

The Ontological Key: Automatically Understanding and Integrating Forms to Access the Deep Web

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Abstract Forms are our gates to the web. They enable us to access the deep content of web sites. Automatic form understanding provides applications, ranging from crawlers over meta-search engines to service integrators, with a key to this content. Yet, it has received little attention other than as component in specific applications such as crawlers or meta-search engines. No comprehensive approach to form understanding exists, let alone one that produces rich models for semantic services or integration with linked open data.

In this paper, we present OPAL, the first comprehensive approach to form understanding and integration. We identify form labeling and form interpretation as the two main tasks involved in form understanding. On both problems OPAL pushes the state of the art: For form labeling, it combines features from the text, structure, and visual rendering of a web page. In extensive experiments on the ICQ and TEL-8 benchmarks and a set of 200 modern web forms OPAL outperforms previous approaches for form labeling by a significant margin. For form interpretation, OPAL uses a schema (or ontology) of forms in a given domain. Thanks to this domain schema, it is able to produce nearly perfect ($> 97\%$ accuracy in the evaluation domains) form interpretations. Yet, the effort to produce a domain schema is very low, as we provide a Datalog-based template language that eases the specification of such schemata and a methodology for deriving a domain schema largely automatically from an existing domain ontology. We demonstrate the value of OPAL’s form interpretations through a light-weight form integration system that successfully translates and distributes master queries to hundreds of forms with no error, yet is implemented with only a handful translation rules.

1 Introduction

Unlocking the vast amount of data in the deep web for automatic processing has been a central part of “web as a database” visions in the past. The web offers unprecedented choice and variety of products, but we lack tools to make these wealth of offers easily manageable. Say you are looking for a flat. *Aren’t you tired of filling registration forms with your search criteria on the websites of hundreds of local agencies? You fear to miss the site with the very best offer? Wouldn’t you wish to automatize these tiresome tasks?* To unlock this data for automatic processing requires two keys: a key that allows us through the human-centric, scripted form interfaces of the web and a key to identify offers among all the other data on the web. In this paper, we focus on the former: A key to web forms, the gates to the deep web. Since these gates are designed for human admission, they pose a plethora of challenges for automatic processing: Even web forms within a single domain denote search criteria differently, e.g., “address”, “city”, “town”, and “neighborhood” all refer to locations, while other terms denote different criteria ambiguously, e.g., “tenure” might refer to the choice either between “freehold” vs. “leasehold” or between “buy” vs. “rent”. Moreover, web forms present their criteria in different manners, e.g., for a choice among several options, a form may contain either a drop-down lists or a set of check boxes. Automatically understanding these variants to pass through forms is needed by a broad range of applications: crawling and surfacing the deep web [27, 20, 8], interface and service integration [35], matching interfaces across domains [7, 32], classifying the domain of web databases [4] for web site classification, sampling the contents of web databases [21, 2], ontology enrichment and knowledge-base construction [25], question answering for the deep web [19]. In web engineering, automated form understanding contributes, e.g., to web accessibility and us-

ability [16], web source integration [10], automated testing on form-related web applications.

The form understanding problem has attracted a number of approaches [35, 32, 10, 23, 17], for a recent survey see [18, 11]. These approaches turn observations on common features of web forms (in general, across domains) into specifically tailored algorithms and heuristics, but generally suffer from three major limitations:

(1) Most approaches are *domain independent* and thus limited to observations that hold for forms across all domains. This limitation is acknowledged in [35, 23, 17], but addressed only through domain specific training data, if at all. Our evaluation supports [17] in that a set of generic design rules underlies all domains, but that specific domains parameterise or adapt to these rules in ways uncommon to other domains.

(2) Most approaches are limited in the *classes of features* they use in their heuristics and often based on a single sophisticated heuristics using one class of features, e.g., only visual features [10] or textual and field type features in [17].

(3) Heuristics are translated into monolithic algorithms limiting maintainability and adaptability. For example, [32] and [23] encode specific assumptions on the spatial distance and alignment of fields and labels, [17] employs hard-coded token classes for certain concepts such as “min”, “from” vs. “max”, “to”.

To overcome these limitations, we present OPAL (**ontology based web pattern analysis with logic**), a domain-aware form understanding system that combines visual, textual, and structural features with a thin layer of domain knowledge. The visual, textual, and structural features are combined in a domain-independent analysis to produce a highly accurate form labeling. However, for most applications what is actually needed is a form model consistent with a (reference) schema of the forms in the given domain, where all the fields are associated with given types. In OPAL, the domain schema is not only used to classify the fields and segments of the form model, but also to improve the form model based on a set of structural constraints that describe typical fields and their arrangement in forms of the domain, e.g., how price ranges are presented in forms. To ease the development of these domain ontologies, OPAL extends Datalog with templates to enable reuse of common form patterns in forms, e.g., how ranges (of any type) are presented in forms. With this approach, OPAL achieves nearly perfect analysis results (> 97% accuracy).

In contrast to previous approaches, OPAL produces rich form models, typed to the given domain schema: The models contain not only types (and individual) constraints for form fields, but group those fields into semantic segments, possibly with inter-field constraints. These rich models ease the development of applications that interact with these forms. To demonstrate this, we have developed a light-

weight form integration system on top of OPAL that fully automatically translates queries to the domain schema into queries to the concrete forms.

1.1 Contributions

OPAL’s main contributions are:

(1) *Multi-scope domain-independent analysis* (Section 3) that combines structural, textual, and visual features to associate labels with fields into a form labeling using three sequential “scopes” increasing the size of the neighbourhood from a subtree to everything visually to the left and top of a field. (i) At *field* scope, we exploit the structure of the page between fields and labels; (ii) at *segment* scope, observations on fields in groups of similar fields, and (iii) at *layout* scope, the relative position of fields and texts in the visual rendering of the page. We impose a strict preference on these scopes to disambiguate competing labelings and to reduce the number of fields considered in later scopes.

(2) *Domain awareness*. (Section 4) OPAL is domain-aware while being as domain-independent as possible without sacrificing accuracy. This is based on the observation that generic rules contribute significantly to form understanding, but nearly perfect accuracy is only achievable through an additional layer of domain knowledge. To this end, we add an optional, domain-dependent classification and form model repair stage after the domain-independent analysis. Driven by a domain schema, OPAL classifies form fields based on textual annotations of their labels and values assigned in the domain-independent form labeling, as well as the structure of that form labeling. This classification is often imperfect due to missing or misunderstood labels. OPAL addresses this in a repair step, where structural constraints are used to disambiguate and complete the classification and reshape the form segmentation.

(3) *Template Language* OPAL-TL. (Section 4.1) To specify a domain schema, we introduce OPAL-TL. It extends Datalog to express common patterns as parameterizable templates, e.g., describing a group consisting of a minimum and maximum field for some domain type. Together with some convenience features for querying the field labeling and its annotations, OPAL-TL allows for very compact, declarative specification of domain schemata. We also provide a template library of common phenomena, such that the adaption to new domains often requires only instantiating these templates with domain specific types. OPAL-TL preserves the complexity of Datalog.

(4) *Methodology for Deriving Domain Schemata*. (Section 4.4) To ease the derivation of an OPAL domain schema, we present a simple, step-by-step methodology how to derive such a schema from a standard domain ontology. It is based on the observation that often the types of the proper-

Figure 1 consists of three panels illustrating the Colin Mason website's search form and its analysis by OPAL.

(a) Full search form (highlighting added): This panel shows the original search form with fields highlighted by red boxes and numbered 1 through 10. The fields are: (1) Location/Postcode/Keyword, (2) Property Type, (3) Bedrooms, (4) Price (Min/Max), (5) Sales or Lettings, (6) Order list by, (7) Show properties as, (8) Property posted within, (9) Properties per page, and (10) Submit button.

(b) Labeling 1: Field labels: This panel shows the same form with labels assigned to each field. The labels are: Location/Postcode/Keyword, Property Type, Bedrooms, Price, Sales or Lettings, Order list by, Show properties as, Property posted within, Properties per page, and Submit.

(c) Interpretation: This panel shows the interpreted labels for each field, categorized into groups: location, property type, bedroom number, price, sales, lettings, order-by, display method, posted within, pagination, and submit button.

Fig. 1: Colin Mason with OPAL (see Figure 2 for segment scope)

ties (such as price or mileage of a car) in the domain ontology determine the configuration of form fields for that type.

(5) *Light-weight Form Integration.* (Section 5) To demonstrate the value of OPAL's rich form models, we implement a form integration system on top of OPAL that automatically translates a master query to hundreds of concrete forms. As shown in the evaluation, even with rather simple translation rules, we achieve accurate form filling.

(6) *Extensive Evaluation.* (Section 6) In an evaluation on over 700 forms of four different datasets, we show that OPAL achieves highly accurate ($> 95\%$) form labelings and, with a suitable domain schema, near perfect accuracy in form classification ($> 97\%$). To compare with existing approaches (which only perform form labeling), we show that OPAL's domain-independent analysis achieves 94 – 100% accuracy on the ICQ benchmark and 92 – 97% on TEL-8. Thus, even without domain knowledge OPAL outperforms existing approaches by at least 5%. We also show that the form integration system developed on top of OPAL is able to fill forms correctly in nearly all cases ($> 93\%$)

We believe that OPAL offers a comprehensive solution to form understanding for most applications, but also discuss, in Section 8, the two major remaining challenges for OPAL (and form understanding, in general): highly scripted, interactive forms, increasingly also using customised form widgets, as well as richer integrity constraints and access restrictions, in particular for applications that aim to extract all of the data behind a form.

This paper is based on [12], but has been significantly extended in every part, in particular in the following three aspects: First, OPAL-TL is only sketched in [12]. Section 4 is the first formal definition of OPAL-TL, including a full rewriting semantics. It has also been extended significantly, most importantly in the supported template features (predicate variables and template groups). Second, we have added a more detailed description of an OPAL domain schema and form model to better illustrate how OPAL operates and what the output of form understanding looks like. Finally, we have implemented a full, though light-weight, form integration and filling system on top of OPAL (Section 5) to demonstrate the value of OPAL's rich models. We have also significantly extended the evaluation to show the results of the form integration, as well as to discuss where and why a small portion of forms still pose a challenge to OPAL.

1.2 OPAL: A Walkthrough

We present the OPAL approach to form understanding using the form from the UK real estate agency Colin Mason (cmea.co.uk/properties.asp). Figure 1a shows the web page with its simplified CSS box model. The page contains two forms (center and left): one for detailed search and the other for quick search. OPAL is able to identify, separate, label, and classify both forms correctly yielding two (real-estate) form models. The following discussion focuses on

(a) Segmentation

(b) Labeling 2a: Segments

(c) Labeling 2b: Fields by Segment

Fig. 2: Colin Mason segment scope

the search form in the center of Figure 1a, in which each of the components (1)-(10), each of the fields (3)-(7) and the two columns of checkboxes in (2) are enclosed in a table, tr, or td element. Labels for each of the components such as “Bedrooms:” appear in separate tr’s.

OPAL’s form understanding operates in two parts: Form labeling and form interpretation. In the form labeling phase fields and groups of fields (called segments) are assigned text labels. In the form interpretation phase those text labels are used to classify the fields and segments on the page, eventually verifying and repairing the label assignment and producing a form model in line with the given domain schema. Form labeling itself is split into field, segment, and layout scope, each assigning successively labels to more fields and segments of a form.

Field scope. (Section 3.1) OPAL starts by analysing individual fields assigning labels in two ways: First, we add labels that explicit reference the field (using the for attribute). Second, we add labels where the common ancestor with a field has no other fields as descendant. In our example from Figure 1a, no explicit references occur, but the second approach correctly labels all fields except the checkboxes in (2). In Figure 1b we show this initial form labeling using same color for fields and their labels.

Segment scope. (Section 3.2) In segment scope, we increase the scope of the analysis from form fields to groups of similar fields (called *segments*). OPAL constructs these segments from the HTML structure, but eliminates segments that likely have no semantic relevance and are only introduced, e.g., for formatting reasons. This elimination is primarily based on semantic similarity between contained fields approximated via semantic attributes such as class and visual similarity. In our example, components (2)-(7) become segments, with (2) further divided into two segments for each of the vertical checkbox groups, as shown in Figure 2a. This rough, approximate segmentation may later be corrected in the form interpretation.

For each *segment as a whole*, OPAL associates text nodes to create segment labels. Segment labels can be useful to repair the form model and to classify fields that have no labels otherwise. In this example, OPAL assigns the text in bold face appearing atop each segment as the label, e.g., “Price:” becomes the label for (4), see Figure 2b. Furthermore, *within* each segment, OPAL identifies repeated groups of interleaving fields and texts. In the example, each check box in (2) is labeled with the text appearing after it, as shown in Figure 2c.

Layout scope. (Section 3.3) In the layout scope, OPAL further enlarges the scope of the analysis to all fields visually to the left and above a field. The primary challenge in this scope is “overshadowing”, i.e., if other fields appear in the quadrants to the left and above a field. In this example the layout scope is not needed.

The result of the layout scope is the form labeling. Notice, that the form labeling is entirely domain independent.

Domain scope. If a form model is required, the final step in OPAL produces a *form model* that is consistent with a given domain schema. How to derive such a domain schema and the necessary annotators is discussed in Section 4.4. It uses domain knowledge to classify and repair the labeling and segmentation from the form labeling. In the classification step, OPAL annotates fields and segments with types based on annotations of the text labels. The verification step repairs and verifies the domain model if needed. For both steps, OPAL uses constraints specified in OPAL-TL. These constraints model typical representations of types in a domain. E.g., the first field in (4) is classified as `MIN_PRICE` as we recognise this segment as an instance of a price range template. These constraints also disambiguate between multiple, conflicting annotations, e.g., fields in (6) are annotated with *order_by* and *price*, but the *price* annotation is disregarded due to the group label. Even without the group label, *price* would be disregarded as the domain schema gives precedence to *order_by* over *price* due to the observation that if they occur together, the field is likely about “order by price” and not about actual prices. Finally, a single repair is performed in this case: We collapse the two checkbox segments in (2) as they are the only children of their parent segment and both of the same type. Figure 1c shows the final field classification as produced by OPAL.

Form integration and filling. Using the form interpretation constructed in the preceding stages, OPAL is able to map a master query formulated on the domain schema into both of the concrete forms on this page (see Figure 1a). For location, the values are typed in directly. For price, the range in the master query can also be directly entered, as the concrete forms use text inputs for prices and OPAL’s form interpretation identifies the min and max price field successfully. For the bedroom number, the value from the master query is compared with the members of the check box list and the most similar is selected.

2 Approach

OPAL constructs a model of a form consistent with a *domain schema*. A domain schema describes how forms in a given conceptual domain, such as the UK real estate domain, are structured. OPAL divides this problem (“form understanding”) into *form labeling* and *form interpretation*. The form labeling identifies forms and their fields, arranges the fields

into a tree, and labels the found fields, segments, and forms with text nodes from the page. The form interpretation aligns a form labeling with the given domain schema and thereby classifies the form fields based on their labels.

2.1 Problem Definition

Form Labeling. A **web page** is a DOM tree $P = ((U)_{U \in \text{Unary}}, R_{\text{child}}, R_{\text{next-sibl}}, R_{\text{attribute}})$ where $(U)_{U \in \text{Unary}}$ are unary type and label relations, R_{child} is the parent-child, $R_{\text{next-sibl}}$ the direct next sibling, and $R_{\text{attribute}}$ the attribute relation. Further XPath relations (such as descendant) are derived from these basic relations as usual [6]. U contains relations for types as in XPath (element, text, attribute, etc.) and three kinds of label relations, namely tag^l for tags of elements and attributes, text^l for text nodes containing string l , and box^b for elements with bounding box b in a canonical rendering of the page. For consistency with elements, we represent the value of an attribute as text child node of the attribute.

Definition 1 A **form labeling** of a web page P is a tree F with functions \mathfrak{Re} (representative) and \mathfrak{La} (label), such that \mathfrak{Re} maps the nodes of F into P . Leafs in F are mapped to form fields and inner nodes to *form segments*, that is a DOM element grouping a set of fields. Each node n in F is also mapped to a set $\mathfrak{La}(n)$ of text nodes, the *labels* of n .

A node can be labeled with no, one, or many labels via \mathfrak{La} . The form labeling contains a representative (via \mathfrak{Re}) for each form. A representative contains all fields (and segments) of that form. This allows OPAL to distinguish multiple forms on a single page, even if no form element is present or multiple forms occur in a single form element.

Definition 2 Given a web page P , the **form labeling problem** (or schema-less form understanding problem) asks for a form labeling F where for each form f in P

- (1) there is a node $r \in F$ such that $\mathfrak{Re}(r)$ is a suitable representative of f and
- (2) for each field e in f , there exists a leaf node $n_e \in F$ such that n_e is a descendant of r and $\mathfrak{Re}(n_e) = e$ where $\mathfrak{La}(n_e)$ is a suitable label set for e .
- (3) for each inner node s in F (form segment), $\mathfrak{La}(s)$ is a suitable set of labels for the set of fields contained in s .

The suitability of a form representative $\mathfrak{Re}(r)$ and a label set $\mathfrak{La}(n_e)$ is not defined formally, but needs to be evaluated by human annotators (which this, after all, aims to simulate). Our evaluation (Section 6) shows that OPAL produces form labelings F_f that match the gold standard in nearly all cases ($> 95\%$ without using any domain knowledge).

We call a form labeling *complete* for a web page, if, for all e , $\mathfrak{La}(n_e)$ contains *all* text nodes suitable as labels for e . Finding such a form labeling is correspondingly called the *complete form labeling problem*.

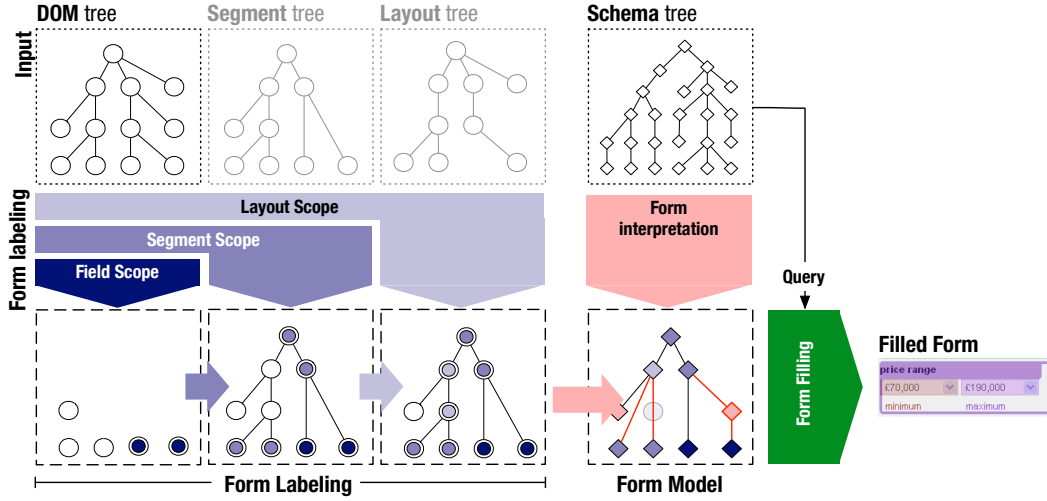


Fig. 3: OPAL Overview

Form Interpretation. To define the form interpretation problem, we formalize the notion of domain schema and introduce a form model as a form labeling extended with type information consistent with a given domain schema. First, we define the part of a domain schema that provides the necessary knowledge to interpret text nodes (“annotation schema”):

Definition 3 An **annotation schema** $\Lambda = (\mathcal{A}, \sqsubset, \prec, (\text{isLabel}_a, \text{isValue}_a : a \in \mathcal{A}))$ defines a set \mathcal{A} of annotation types, a transitive, reflexive subclass relation \sqsubset , a transitive, irreflexive, antisymmetric precedence relation \prec , and two characteristic functions isLabel_a and isValue_a on text nodes for each $a \in \mathcal{A}$.

For each annotation type $a \in \mathcal{A}$, we distinguish *proper labels* and *values*, with isLabel_a and isValue_a as corresponding characteristic functions. Proper labels are text nodes, such as “Price:”, describing the field type; values, such as “more than £500”, contain possible values of the field. Hence $\text{isLabel}_{\text{price}}$ (“Price:”) and $\text{isValue}_{\text{price}}$ (“more than £500”) hold.

The \sqsubset relation holds for subtypes, e.g., $\text{postcode} \sqsubset \text{location}$, and the \prec relation defines precedence on annotation types used to disambiguate competing annotations. For example, an unlabeled select box with options “Choose sorting order”, “By price”, and “By postcode” may be annotated with *order-by*, *price*, and *postcode*. If $\text{order-by} \prec \text{price}$ and $\text{order-by} \prec \text{postcode}$, we pick *order-by*.

Definition 4 A **domain schema** $\Sigma = (\Lambda, \mathcal{T}, \rightarrow, \mathcal{C}_{\mathcal{T}}, \mathcal{C}_{\Lambda})$ defines an annotation schema Λ , a set of domain types \mathcal{T} with (transitive, reflexive) part-of relation \rightarrow , and $\mathcal{C}_{\mathcal{T}}$ and \mathcal{C}_{Λ} that map domain types to classification and structural constraints.

For example, $\mathcal{C}_{\Lambda}(\text{PRICE})$ requires an annotation *price* and prohibit any annotation of a type with precedence over *price* (such as *order-by* above). The set of structural constraints

$\mathcal{C}_{\mathcal{T}}(\text{PRICE-RANGE})$ for a PRICE-RANGE segment requires a MIN-PRICE and MAX-PRICE field or a PRICE-RANGE field. We write $S \models C$, if a constraint set C is satisfied by a set S of annotation or domain types. The empty constraint set is always satisfied. \rightarrow plays an important role in the definition of the constraints, as it prescribes the structure of the types in the domain. For details on constraints and how to define them, see Section 4.

Formally, a *form interpretation* (F, τ) is a form labeling F with a partial type-of relation τ , relating nodes in F with the types \mathcal{T} of Σ . Given a node n in F , we denote with $\mathcal{A}(n) = \{a \in \mathcal{A} : \exists l \in \mathcal{L}_F(n) \text{ with } \text{isValue}_a(l) \text{ or } \text{isLabel}_a(l)\}$ the set of annotation types associated with n via its labels, and with $\text{child-}\mathcal{T}(n) = \bigcup_{(n,n') \in F} \tau(n')$ the set of domain types of the children of n .

Definition 5 A form interpretation (F, τ) is a **form model** for Σ , iff $\mathcal{A}(n) \models \mathcal{C}_{\Lambda}(t)$ and $\text{child-}\mathcal{T}(n) \models \mathcal{C}_{\mathcal{T}}(t)$ for all $n \in F$, $t \in \tau(n)$.

Definition 6 Given a domain schema Σ and a form labeling F , the **form interpretation problem** asks for a form model (F', τ) for Σ such that F' differs from F only in inner nodes. Thus, form representatives, fields, and labels are shared between F and F' , but the form segments may be rearranged to conform with the structural constraints of Σ .

Definition 7 Given a domain schema Σ and a web page P , the (schema-based) **form understanding problem** asks for a form model (F, τ) of P under Σ , such that F is a solution of the complete form labeling problem for P .

Form Integration and Filling. In web interface integration a query against a global domain schema is translated and executed on concrete forms. The returned data is translated into the domain schema and returned. We focus here on the

first part of the integration problem, the query translation or *form integration* problem, and more specifically on its optimistic variant:

Let Σ be a domain schema. Then a query Q on Σ is a set of unary constraints on \mathcal{T} , the domain types in Σ . We consider three types of constraints: (1) *Equality constraints* such as $\text{POSTCODE} = \text{OX1}$; (2) *range constraints* such as $\text{PRICE} \in [700, 1250]$; (3) *inclusion constraints* such as $\text{COLOUR} \in \{\text{red}, \text{green}, \text{black}\}$.

Definition 8 Given a domain schema Σ , a query Q on Σ , and a concrete form F , the **form integration problem** is the problem to translate Q into a (single) query Q' on F such that Q' returns all results that match Q and can be retrieved by F and that there is no other query on F with that property that returns less results.

Note, that we do not require that Q' returns only results that match Q , but that its result set is minimal among all queries on F that return all matches for Q that can be retrieved by F . This is necessary, as there may be no query on F that is able to exactly express Q .

2.2 OPAL Architecture

OPAL is divided into three parts. Of those, two form OPAL's form understanding: a domain-independent part to address the form labeling problem and a domain-dependent part for form interpretation according to a domain schema. The remaining part is devoted to form integration and translates queries against a domain schema into queries on concrete forms.

OPAL produces form labelings in a novel multi-scope approach that incrementally constructs a form labeling combining textual, structural, and visual features (Figure 3). Each of the three labeling scopes considers features not considered in prior scopes:

- (1) In *field scope*, we consider only fields and their immediate neighbourhood and thus use only the DOM tree as input.
- (2) In *segment scope*, we detect and arrange form segments into a segment tree to interleave the contained text nodes and fields.
- (3) In *layout scope*, we broaden the potential labels of a field by searching in the layout tree, i.e., the visual rendering of the page, and assign text nodes to fields, given a strong visual relation.

Each scope builds on the partial form labeling of the previous scope and uses the information from the additional input to find labels for previously unlabeled fields (or segments). Only the segment scope adds nodes, namely form segments, whereas field and layout scope only add labels.

Finally, in the (4) *form interpretation* (Section 4) we turn the form labeling produced by the first three scopes

Algorithm 1: FieldScopeLabelling($DOM P$)

```

1 foreach field  $f$  in  $P$  do
2    $n \leftarrow f$ ;
3   while  $n$  has a parent do
4     if  $n$  is already coloured then colour  $n$  red; break;
5     colour  $n$  orange;
6      $n \leftarrow$  parent of  $n$ ;
7  $F \leftarrow$  empty form labeling ;
8 foreach field  $f$  in  $P$  do
9    $n \leftarrow$  new leaf node in  $F$ ;
10   $\Re(n) \leftarrow f$ ;
11  if  $\exists l \in P$  with for attribute referencing  $f$  then
12    assign all text node descendants of  $l$  as labels to  $n$  ;
13   $p \leftarrow$  parent of  $f$ ;
14  while  $p$  not coloured red do
15     $f \leftarrow p$ ;  $p \leftarrow$  parent of  $f$ ;
16  assign all text node descendants of  $f$  as labels to  $n$  ;

```

into a form model consistent with a given domain schema.

- (i) The labeling model is extended with (domain-specific) annotations on the textual content of proper labels and values.
- (ii) Fields and segments of the form labeling are classified according to classification constraints in the domain schema.
- (iii) Finally, violations of structural schema constraints are repaired in a top-down fashion.

Types and constraints of the domain schema are specified using OPAL-TL, an extension of Datalog that combines easy querying of the form labeling and of annotations with a rich template system. Datalog rules already ease the reuse of common types and their constraints, but the template extension enables the formulation of generic templates for such types and constraints that are instantiated for concrete types of a domain. An example of a type template is the range template, that describes typical ways for specifying range values in forms. In the real estate domain it is instantiated, e.g., for price and various room ranges. In the used car domain, we also find ranges for engine size, mileage, etc. Thus, creating a domain schema is in many cases as easy as importing common types and instantiating templates, see in Section 4.

The form understanding part of OPAL is complemented with a form integration part, where we translate a given query on the domain schema into queries on concrete forms. To do so, we construct an OPAL form model as above and then use that form model to map the constraints of the given query to fields on the concrete form. The form is then filled according to the constraints. Where a constraint can not be mapped precisely, we use standard similarity techniques to find the closest, inclusive option (in case of numerical types) or just the closest option (in case of categorical types), see Section 5.

3 Form Labeling

In OPAL, form labeling is split into three scopes. Each scope is focused on a particular class of features (e.g., visual, structural, textual). The form labeling scopes, *field*, *segment*, and *layout* scope, use **domain-independent** labeling techniques to associate form fields or segments with textual labels, building a form labeling F . If a domain schema is available, the form labeling is extended to a form model in the domain-dependent analysis (Section 4).

The form labeling F is constructed bottom-up, applying each scope’s technique in sequence to yet unlabelled fields. Whenever a field is labelled at a certain scope level, further scopes do not consider this field again. This precedence order reflects higher confidence in earlier scopes and addresses competing label assignments.

3.1 Field Scope

Based on the DOM tree of the input page, the **field scope** assigns text nodes in a unique structural relation to individual fields as labels to these fields (see Algorithm 1). It relies on the observation that, if a text node shares a sub-tree of the DOM with a single field only, then that text node is most likely related to that field. This simple observation produces a significant portion of form labels, as shown in Section 6, and is designed to produce nearly no false positives, as also verified in Section 6.

Specifically, Algorithm 1 (1) colours (lines 1–6) all nodes in P that are ancestors of a field and do not have other form fields as descendants in orange. The least ancestor that violates that condition is coloured red. (2) It identifies (line 7–10) all form fields and initialises the form labeling F with one leaf node for each such field. (3) It considers (lines 11–12) explicit HTML label elements with *direct reference* to a form field. (4) It labels (lines 13–16) each field f with all text nodes t whose *least common ancestor* with f has no other form field as descendant. This includes all text nodes t in the content of f such as its values (in case of select, input, or textarea elements), since the least common ancestor of t and f is f itself. We find these text nodes in linear time due to the tree colouring.

3.2 Segment Scope

At **segment scope**, the labeling analysis expands from individual fields to form segments, i.e., groups of consecutive fields with a common parent, forming the segment tree (Algorithm 2). These segments are then used to distribute text nodes to unlabeled fields in that segment (Algorithm 3). At this scope, we approximate form segments through the DOM structure and the style of the contained fields. This

Algorithm 2: SegmentTree($DOM P$)

```

1  $P' \leftarrow P$ ;
2 while  $\exists n \in P' : n \text{ not a field} \wedge (\nexists \text{ field } d : R_{\text{descendant}}(d, n) \in P')$ 
   do
3   delete  $n$  and all incident edges from  $P'$ ;
4 while  $\exists n \in P' : |\{c \in P' : R_{\text{child}}(c, n) \in P'\}| = 1$  do
5   delete  $n$  from  $P'$  and move its child to the parent of  $n$ ;
6 foreach inner node  $n$  in  $P'$  in bottom-up order do
7    $C \leftarrow \{f : R_{\text{child}}(f, n) \in P' \wedge f \text{ is a field}\}$ ;
8    $C \leftarrow C \cup \{\text{Representative}(n') : R_{\text{child}}(n', n) \in P'\}$ ;
9   choose  $r \in C$  arbitrarily;
10  if  $\forall r' \in C : r \text{ style-equivalent to } r'$  then
11     $\text{Representative}(n) \leftarrow r$ ;
12    delete all non-field children of  $n$  and move their
    children to  $n$ ;
13  else  $\text{Representative}(n) \leftarrow \perp$ ;
14 return  $P'$ ;

```

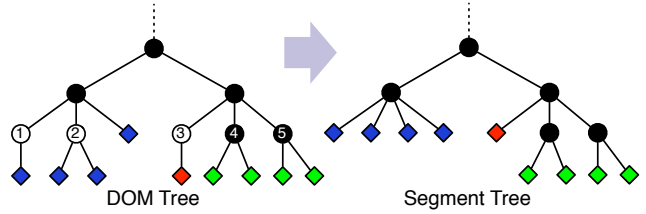


Fig. 4: Example DOM and Segment Tree

segmentation is later adjusted to yield only form segments with a clear semantic. It is worth noting, that on many forms only very few adjustments are necessary, supporting the veracity of the approximation of semantic segments through structure and style.

Segmentation tree. We observe that the DOM is often a fair, but noisy approximation of the semantic form structure, as it reflects the way the form author grouped fields into segments. Therefore, we start from the DOM structure to find the form segments, but we eliminate all nodes that can be safely identified as superfluous: nodes without field descendants, nodes with only one child, and nodes n where all fields in n are style-equivalent to the fields in the siblings of n . Two fields are **style-equivalent** if they carry the same class attribute (indicating a formatting or semantic class) or the same type attribute and CSS style information.

If all field descendants of the parent of an inner node n are style-equivalent, then n should be eliminated from the segment tree, as it artificially breaks up the sequence of style-equivalent fields and is thus *equivalence breaking*.

Definition 9 The **segment tree** P' of a form page P is the maximal DOM tree included in P (i.e., obtained by collapsing nodes) such that the leaves of P' are all fields and, for all its inner nodes n ,

- (1) $|\{c \in P' : R_{\text{child}}(c, n)\}| > 1$,
- (2) n is not equivalence breaking.

As an example, consider the DOM tree on the left of Figure 4, where diamonds represent fields and style-equivalent fields carry the same colour. On the right hand side, we show OPAL's segment tree for that DOM. Nodes 1 and 3 from the original DOM are eliminated as they have only one child, and node 2 as it is equivalence breaking. Nodes 4 and 5 are retained due to the red field.

Theorem 1 *The segment tree P' of a web page P can be computed in $O(n \times d)$ with n size and d depth of P .*

Proof Algorithm 2 computes the segment tree P' for any DOM tree P . Its leafs are fields (as any non field leafs are eliminated in line 2–3) and any inner node must have more than 1 child (due to line 4–5), a field descendant (due to line 2–3), and not be equivalence breaking (due to lines 6–13). In lines 6–13, we compute a Representative, bearing the style prevalent among the inner node's fields, for each inner node in a bottom-up fashion: If all field children (line 7) and the representatives of all inner children (line 8) are style-equivalent (line 9–10), we choose an arbitrary representative and collapse all inner children of that node. Note, that it suffices to compare any of the representatives with the fields in C as style-equivalence is transitive. Otherwise, we assign \perp as representative, which is style-equivalent neither to any node nor to itself. Thus it prevents this node (and its ancestors) from ever being collapsed. By construction, these nodes respect (1) and (2) and this property is retained in all later steps, as their subtrees are never touched again.

P' is maximal: Any tree P'' that includes P' but is included in P must contain at least one node from P that has been deleted by one of the above conditions. Such a node, however, violates at least one of the conditions for a segment tree and thus P'' is not a segment tree. This holds because the order of the node deletions does not affect the nodes deleted.

Algorithm 2 runs in $O(n \times d)$: Lines 2–3 are in $O(n)$. Lines 4–5 and lines 6–13 are both in $O(n \times d)$ as they are dominated by the collapsing of the nodes. At most, we collapse $d - 2$ inner nodes and move $O(n)$ leaves $d - 2$ times.

Segment Labeling. We extend the existing form labeling F of the field scope with form segments according to the structure of the segment tree and distribute labels in regular groups, see Algorithm 3. First (lines 2–5), we create a form segment node s in the form labeling for each inner node n_s in the segment tree and choose n_s as representative for s ($\mathcal{R}e(s) = n_s$). For each segment with regular interleaving of text nodes with field or segment nodes, we use those text nodes as labels for these nodes, preserving any already assigned labels and fields (from field scope). In detail, we iterate over all descendants c of each segment in document order, skipping any nodes that are descendants of another

Algorithm 3: SegmentLabeling($DOM P, Form Labeling F$)

```

1  $S \leftarrow \text{SegmentTree}(P)$ ;
2 foreach inner node  $s$  in  $S$  in bottom-up order do
3   create a new segment  $n_s$  in  $F$ ;
4    $\mathcal{R}e(n_s) \leftarrow s$ ;
5   create an edge  $(n_s, c_s)$  in  $F$  for every  $\mathcal{R}e(c_s)$  child of  $s$ ;
6 foreach segment  $n$  in  $F$  do
7    $\text{Nodes}, \text{Labels} \leftarrow \text{new List}()$ ;
8    $\text{textGrp} \leftarrow \emptyset$ ;
9   foreach  $c : \mathcal{R}_{\text{descendant}}(c, \mathcal{R}e(n)) \in P$  in document order do
10    if  $\exists f \in F : \mathcal{R}e(f) = c \wedge \mathcal{L}a(f) = \emptyset$  then
11      if  $\text{textGrp} \neq \emptyset$  then  $\text{Labels.add}(\text{textGrp})$ ;
12       $\text{textGrp} \leftarrow \emptyset$ ;
13       $\text{Nodes.add}(c)$ ;
14      skip all descendants of  $c$  in the iteration ;
15    else if  $c$  is a text node  $\wedge \nexists d \in F : c \in \mathcal{L}a(d)$  then
16       $\text{textGrp} \leftarrow \text{textGrp} \cup \{c\}$ ;
17 if  $\text{textGrp} \neq \emptyset$  then  $\text{Labels.add}(\text{textGrp})$ ;  $\text{textGrp} \leftarrow \emptyset$ ;
18 if  $\text{Labels.size}() = \text{Nodes.size}() + 1$  then
19   add  $\text{Labels}[0]$  to  $\mathcal{L}a(n)$ ;
20   delete  $\text{Labels}[0]$  from  $\text{Labels}$ ;
21 if  $\text{Labels.size}() = \text{Nodes.size}()$  then
22   foreach  $i$  do add  $\text{Labels}[i]$  to  $\mathcal{L}a(\text{Nodes}[i])$ ;

```

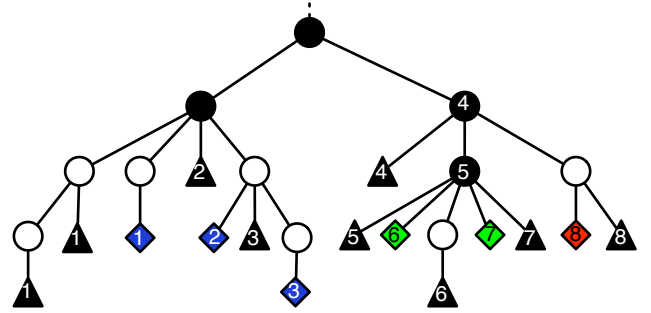


Fig. 5: Example for Segment Scope Labeling

segment or field itself contained in n (line 13). In the iteration, we collect all field or segment nodes in Nodes , and all sets of text nodes between field or segment nodes in Labels , except those already assigned in field scope (line 14), as we assume that these are outliers in the regular structure of the segment. We assign the i -th text node group to the i -th field, if the two lists have the same size (possibly using the first group as labels of the segment, line 17–19).

Figure 5 illustrates the segment scope labeling with triangles standing for text nodes, diamonds for fields, black circles for segments, and white circles for DOM nodes not in the segment tree. The numbers indicate which text nodes are assigned as labels to which segments or fields. E.g., for the left hand segment, we observe a regular structure of (text node+, field)+ and thus we assign the i -th group of text nodes to the i -th field. For the right hand segment (4), we find a subsegment (5) and field 8 that is already labeled with text node 8 in the field scope. Thus 8 is ignored and only one text node remains directly in 4, which becomes the segment

label. In 5, we find one more text node group than fields and thus consider the first text node group as a segment label. The remaining nodes have a regular structure (field, text node+)+ and get assigned accordingly.

3.3 Layout Scope

At **layout scope**, we further refine the form labeling for each form field not yet labelled in field or segment scope, by exploring the visible text nodes in the west, north-west, or north quadrant, if they are not overshadowed by any other field. To avoid false positives, we limit this search to the boundaries of the enclosing form. First, OPAL constructs a layout tree from the CSS box labels of the DOM nodes:

Definition 10 The **layout tree** of a given DOM P is a tuple $(N_P, \triangleleft, w, nw, n, ne, e, se, s, sw, aligned)$ where N_P is the set of DOM nodes from P , $\triangleleft, w, nw, n, \dots$ the “belongs to” (containment), west, north-west, north, \dots relations from RCR [22], and $aligned(x, y)$ holds if x and y have the same height and are horizontally aligned.

We call w, nw, \dots the neighbour relations. The layout tree is at most quadratic in size of a given DOM P and can be computed in $O(|P|^2)$. For convenience, we write, e.g., $w-nw-n$ to denote the union of the relations w, nw , and n .

In cultures with left-to-right reading direction, we observe a strong preference for placing labels in the $w-nw-n$ region from a field. However, forms often have many fields interspersed with field labels and segment labels. Thus we have to carefully consider overshadowing. Intuitively, for a field f , a visible text node t is overshadowed by another field f' if t is above f' or also visible from, but closer to f' . In the particular case of aligned fields, the former would prevent any labeling for these fields and thus we relax the condition.

Definition 11 For a given text node t , a field f' **overshadows** another field f if

- (1) f and f' are unaligned, $w-nw-n(f', f)$, and $w-nw-n-ne-e(t, f')$ or
- (2) f and f' are aligned and (i) $w(t, f')$ or (ii) $nw-n(t, f')$ and there is a text node t' not overshadowed by another field with $ne-e(t', f')$ and $w-nw-n(t', f)$.

To illustrate this overshadowing, consider the example in Figure 6. For field F_1 , T_2 and T_4 are overshadowed by F_2 and T_3 by F_3 , only T_1 is not overshadowed, as there is no other text node that is west, north-west, or north from F_1 and not overshadowed by another field.

The layout scope labeling is then produced as follows: For each field f , we collect all text nodes t with $w-nw-n(t, f)$ and add them as labels to f if they are not overshadowed by another field and not contained in a segment that is no ancestor of f . The latter prevents assignment of labels from unrelated form segments.

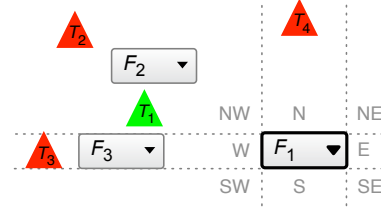


Fig. 6: Layout Scope Labeling

4 Form Interpretation

There is no straightforward relationship between form fields for domain concepts, such as location or price, and their structure within a form. Even seemingly domain-independent concepts, such as price, often exhibit domain-specific peculiarities, such as “guide price”, “current offers in excess”, or payment periods in real estate. OPAL’s domain schemata allow us to cover these specifics. We recall from Section 2 that a form model (F', τ) for a schema Σ is derived from a form labeling F by extending F with types and restructuring its inner nodes to fit the structural constraints of Σ .

OPAL performs form interpretation of a form labeling F in two steps: (1) the *classification* of nodes in F according to the domain types \mathcal{T} to obtain a (partial) typing τ_P . This step relies on the annotation schema Λ and its typing of labels in F ; (2) the *model repair* where the segmentation structure derived in the segmentation scope (Section 3.2) is aligned with the structure constraints of Σ to complete the typing.

The effort for creating an OPAL domain schema may, at the first glance, appear considerable. However, not only do we provide OPAL-TL (Section 4.1) to ease the specification of a domain schema, we also discuss in Section 4.4 how all the artefacts needed by OPAL for a new domain can be nearly automatically derived from a standard ontology of a domain (including concept labels) and a set of entity recognisers (or annotators) for instances of the concepts. We illustrate this methodology for *domain instantiation* along the example of the used car domain.

4.1 Schema Design: OPAL-TL

OPAL provides a **template language**, OPAL-TL, for easily specifying domain schemata reusing common concepts and their constraints as well as concept templates. To implement a new domain, we only need to provide (1) for each annotation type a an annotator implementing $isLabel_a$ and $isValue_a$ and (2) an OPAL-TL specification of the domain types with their classification and structural constraints. The latter can be derived almost mechanically from the domain types as discussed in Section 4.4.

OPAL-TL extends Datalog with template capabilities and predefined predicates for convenient querying of annotations and DOM nodes. An OPAL-TL program is executed against a form labeling F and a DOM P . Relations from F and P are mapped in the obvious way to OPAL-TL. We only use child (descendant, resp.) for the child (descendant, resp.) relation in F . We extend document and sibling order from P to F : $\text{follows}(X, Y)$ for $X, Y \in F$, if $R_{\text{following}}(\mathfrak{Re}(X), \mathfrak{Re}(Y)) \in P$ and no other node in F occurs between X and Y in document order; $\text{adjacent}(X, Y)$, if $R_{\text{next-sibling}}(\mathfrak{Re}(X), \mathfrak{Re}(Y)) \in P$ or vice versa. Finally, we abbreviate $\text{text}^l(\mathfrak{Re}(X))$ and $\text{tag}^l(\mathfrak{Re}(X))$ as $l(X)$ and $t(X)$.

Annotation types and their queries. Annotations (instances of annotation types) are characterised by an external specification of the characteristic functions isLabel_a and isValue_a for each $a \in \mathcal{A}$. In the current version of OPAL, these functions are implemented with simple GATE (gate.ac.uk) gazetteers and transducers, that are either provided by human domain experts or realised by access to external annotators and knowledge bases such as DBpedia and Freebase. Together they provide annotators for common domain types such as price, location, or date. Additional entity recognisers or annotators can be added easily, as described in Section 4.4.

Annotations are used in annotation queries to select fields based on annotations on their labels and the labels of their segments:

Definition 12 For a form labeling F on a DOM P and an annotation schema Λ with annotation types \mathcal{A} , an **OPAL-TL annotation query** is an expression of the form $X@A\{d, p, e, m\}$ where X is a first-order variable, $A \in \mathcal{A}$, and d, p, e , and m are annotation *modifiers*. An annotation query $X@A\mu$ with $\mu \subseteq \{d, p, e, m\}$ holds for $X \in \llbracket A\mu \rrbracket$ with

$$\begin{aligned} \llbracket A\mu \rrbracket &= \{n \in \text{Fields} : M_\mu(A, n) \neq \emptyset\} \setminus \text{Block}_\mu(A) \\ \text{Fields} &= \{n \in P : \exists \text{ leaf } f \in F : n \in \mathfrak{Re}(f)\} \\ M_\mu(A, n) &= \begin{cases} \text{Allowed}_\mu(n) \cap \bigcup_{A' \sqsubset^* A} \text{isLabel}_{A'} & \text{if } p \in \mu \\ \text{Allowed}_\mu(n) \cap \bigcup_{A' \sqsubset^* A} (\text{isLabel}_{A'} \cup \text{isValue}_{A'}) & \text{otherwise} \end{cases} \\ \text{Block}_\mu(A) &= \begin{cases} \{n : \exists A' \neq A : |M_\mu(A, n)| < |M_\mu(A', n)|\} & \text{if } m \in \mu \\ \{n : \exists A' \prec A : |M_\mu(A, n)| < |M_\mu(A', n)|\} & \text{if } e \in \mu \\ \emptyset & \text{otherwise} \end{cases} \\ \text{Allowed}_\mu(n) &= \begin{cases} \mathcal{L}\alpha(n) & \text{if } d \in \mu \\ \mathcal{L}\alpha(n) \cup \mathcal{L}\alpha(\text{parent of } n) & \text{otherwise} \end{cases} \end{aligned}$$

Intuitively, an annotation query $X@A$ returns all fields labeled with a label that is annotated with A . If the modifier d (direct) is *not* present, we also consider the (direct) segment parents, otherwise only *direct* labels are considered. If the modifier p (proper) is present, only isLabel_A is used, otherwise also isValue_A . If the modifier e (exclusive) is present,

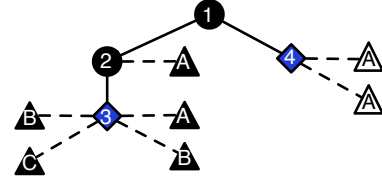


Fig. 7: Example Form Labeling

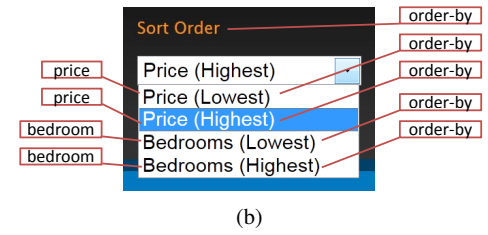
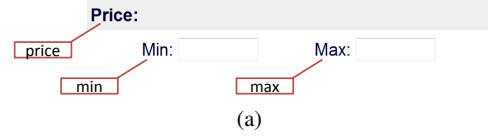


Fig. 8: Label Annotation Examples

a node that fulfils all other conditions is still not returned, if there are more labels with annotations of a type that has precedence over A . If the modifier m (*maximal*) is present, no other type, regardless of precedence, may have more labels with annotations at the node. Since m excludes strictly more nodes than e , a query with both m and e returns the same nodes as that query without e .

Consider the form labeling of Figure 7 under a schema with $B \prec A$. Labels are denoted with triangles, fields with diamonds, segments with circles. Labels are further annotated with matching annotation types (here always only one), with value labels drawn as outlines only. Then, $X@A\{\}$ matches 3, 4; $X@A\{e, d\}$ matches 4, but not 3 as 3 has more labels of B than of A and the exclusive modifier e is present; $X@A\{e, p\}$ matches 3, but not 4 as the proper modifier p prevents the value labels in white to be considered. The latter matches 3 despite the presence of e , as we consider also the labels of the parent of 3 (since the direct modifier d is absent) and thus there are two A labels.

Figure 8 shows a real-life example with the annotations produced by a typical set of annotators. In 8a, there are two text inputs for min and max price. However, the two labels “min” and “max” are the only directly associated text boxes and do not carry any information that indicates that these fields are about prices. This is available only when considering the segment (and thus indirect) label “Price:”. Thus, $X@price\{d\}$ returns the emptyset, but $X@price\{\}$ returns the two fields. In 8b, the drop-down menu for result ordering re-

ceives two price annotations, two bedroom annotations, and five order-by annotations. With *order-by* \prec price, $X @ \text{price}\{e\}$ returns the emptyset, as the price annotations are “blocked” by the order-by annotations.

OPAL-TL templates. OPAL-TL is a Datalog-based language for the definition of reusable templates of domain concepts. Examples of such templates are basic classification rules deriving a domain type from a conjunction of annotation types or min-max range templates where we look for multiple fields with related annotations in a group and some clue that they represent a range. In general, there are two types of such templates, one for classification constraints, one for structural constraints. The former specify relationships between domain and annotation types, the latter the abstract structure of domain concepts.

Definition 13 An **OPAL-TL template** is an expression of the form: **TEMPLATE** $N \langle T_1, \dots, T_k \rangle \{ p_1 \Leftarrow \text{expr}_1, \dots \}$ where N is the template name, T_1, \dots, T_k are template variables, p_1 is a template atom, expr_1 a boolean formula over template atoms and annotation queries. A *template atom* $p \langle \mathbf{t} \rangle (\mathbf{s})$ consists of a first-order predicate p , a sequence of terms $\mathbf{t} = t_1, \dots, t_n$ (where t_i is either a constant or a template variable), and a sequence of terms $\mathbf{s} = s_1, \dots, s_n$ where each s_i is either a constant or a first-order variable. Template and first-order variables constitute two disjoint sets. Note that, if \mathbf{t} is empty, then a template atom is a normal first-order atom. Moreover, when all terms \mathbf{t} are constants, we say that the template atom is *template-ground*.

Multiple rules with the same head can be used to express disjunction of their bodies. For convenience, we use \vee and \neg over conjunctions, which are translated to Datalog⁺ as usual.

As an example, the following template defines a family of constraints that associate the concept (domain type) C to a node N whenever N is labeled by an exclusive direct and proper annotation of type A .

TEMPLATE basic_concept $\langle C, A \rangle \{ \text{concept}\langle C \rangle(N) \Leftarrow N @ A\{d, e, p\} \}$

An *instantiation* of a template tpl produces a set of rules where the template variables C_1, \dots, C_k are assigned to values v_1^i, \dots, v_k^i defined by a *template instantiation* expression of the form:

INSTANTIATE $\text{tpl}\langle T_1, \dots, T_k \rangle \text{ using } \{ \langle v_1^1, \dots, v_k^1 \rangle \dots \langle v_1^n, \dots, v_k^n \rangle \}$

For example, the following expression instantiates basic_concept replacing C with type `RADIUS` and A with annotation type `radius`

INSTANTIATE basic_concept $\langle C, A \rangle \text{ using } \{ \langle \text{RADIUS}, \text{radius} \rangle \}$

and produces the following instantiated rule:

concept $\langle \text{RADIUS} \rangle(N) \Leftarrow N @ \text{radius}\{d, e, p\}$

```

<program> ::= (<template> | <inst> | <trule>)+
<template> ::= 'TEMPLATE' <id> '<' <tvar>+ '>' '{' <trule>+ '}'
<inst>      ::= 'INSTANTIATE' <id> '<' <tvar>+ '>'
              'using' '{' (<'<' <const>+ '>')+ '>' '}'
<trule>     ::= <tatom> '<' <tbody> | <inst>
<tbody>     ::= <texpr> ('<' <texpr>)*
<texpr>     ::= <atom> | <annot> | <tatom> | <neg> | <disj>
<annot>     ::= <var> '@' '{' ('<d' | 'e' | 'p' | 'm')* '}'
<tatom>     ::= <id> '<' (<tvar> | <const>)+ '>' ('<' <par>* '>')
              | '<' <tvar> '>' ('<' <par>* '>')
<par>       ::= <var> | <tvar> | <const>
<const>     ::= <type-id> | <annot-id> | <tag> | <string> | <id>
<neg>       ::= '<' '<' <tbody> '>'
<disj>      ::= '<' <tbody> '<' '<' <tbody> '>'

```

Fig. 9: OPAL-TL syntax

The full syntax of OPAL-TL is given in Figure 9 (with $\langle \text{string} \rangle$, $\langle \text{id} \rangle$, and $\langle \text{var} \rangle$ as in Datalog and $\langle \text{tvar} \rangle$, $\langle \text{type-id} \rangle$, $\langle \text{annot-id} \rangle$, $\langle \text{tag} \rangle$ template variables, domain types, annotation types, and HTML tags, respectively).

The semantics of OPAL-TL is given by rewriting any set of templates Σ_T into Datalog⁺ programs, using assignments of template variables to constants specified by the instantiation rules, and by considering every template-ground predicate name as a new first-order predicate. Due to possible occurrences of **INSTANTIATE** within templates, the instantiation must be repeated until there are no applicable **INSTANTIATE** rules. To ensure termination of the instantiation procedure, we do not allow recursive template instantiations. Properties such as safety can be easily extended from Datalog⁺ to OPAL-TL:

Definition 14 A OPAL-TL template is **safe**, if every template variable that occurs in the body also occurs in the head of the template and every rule is safe, i.e., all first-order variables that occur in the head or in a negative atom in the body, also occur in a positive atom in the body.

Proposition 1 Let Σ_T be a set of safe OPAL-TL templates, and let S be an assignment specified by OPAL-TL instantiation rules, then any instantiation $\tau(\Sigma_T, S)$ is a safe Datalog⁺ program.

In contrast to safety, stratification depends also on the instantiation and is therefore defined over the expanded program as usual.

A natural question is now the complexity of computing the form model using OPAL-TL. This is related to the complexity of *fact inference* in OPAL-TL.

Proposition 2 Fact inference in OPAL-TL is PTIME-complete in data complexity (when Σ_T and S are fixed) and EXPTIME-complete in combined complexity.

```

TEMPLATE concept_by_proper<C,A> {concept<C>(N)  $\Leftarrow$  N@A{d,e,p}}
2
TEMPLATE concept_by_segment<C,A> {concept<C>(N)  $\Leftarrow$  N@A{e,p}}
4
TEMPLATE concept_by_value<C,A> {concept<C>(N)  $\Leftarrow$  N@A{m},
6    $\neg(A_1 \neq A, N@A_1\{d,e,p\} \vee N@A_1\{e,p\})$  }

8 TEMPLATE concept_minmax<C,CM,A> {
  concept<CM1)  $\Leftarrow$  child(N1,G), child(N2,G), adjacent(N1,N2),
10   N1@A{e,d}, (concept<C>(N2)  $\vee$  N2@A{e,d})
  concept<CM2)  $\Leftarrow$  child(N1,G), child(N2,G), follows(N2,N1),
12   concept<C>(N1), N2@range_connector{e,d},  $\neg(A_1 \prec A, N_2@A_1\{d\})$ 
  concept<CM1)  $\Leftarrow$  child(N1,G), child(N2,G), adjacent(N1,N2),
14   N1@A{e,p}, N2@A{e,p}, ((N1@min{e,p}, N2@max{e,p})
     $\vee$  (N1@max{e,p}, N2@min{e,p}))

```

Fig. 10: OPAL-TL classification templates

Proof Consider a set of template atoms D , a set of OPAL-TL templates Σ_T over a set of template predicates \mathcal{R}_T of at most arity k , and an assignment \mathcal{S} of template variables to constants in a set Γ_T specified by OPAL-TL instantiation rules. The *fact inference* problem for D , Σ_T , and \mathcal{S} is to decide whether $D \cup \langle \Sigma_T, \mathcal{S} \rangle \models \underline{a}$, where \underline{a} is a template atom. According to Proposition 1, the problem can be reduced to fact inference in Datalog⁻, i.e., deciding whether $D \cup \Sigma_D \models \underline{a}$ where $\Sigma_D = \tau(\Sigma_T, \mathcal{S})$ is the rewritten program. Clearly, the data complexity is PTIME-complete as for Datalog⁻. Regarding the combined complexity, recall that fact inference for a Datalog⁻ program Σ_D and a set of atoms D is EXPTIME-complete since the maximum number of atoms that can be inferred is $|\mathcal{R}_D| \cdot (\text{dom}(D))^w$ where \mathcal{R}_D is the set of predicates of Σ_D , $\text{dom}(D)$ is the domain of D and w is the maximum arity of predicates in \mathcal{R}_D . The rewriting $\tau(\Sigma_T, \mathcal{S})$ can generate at most $|\mathcal{R}_T| \cdot (\Gamma_T)^k$ template-ground atoms that contribute to the signature of Σ_D . Therefore, the number of atoms that can be generated is $\mathcal{O}(2^k \cdot 2^w)$ that is still exponential. The claim follows.

4.2 Classification

Classification is based on the classification constraints of the domain schema. In OPAL these constraints are specified using OPAL-TL to enable reuse of domain concepts and templates. For instance, in the real estate and used car domains, we identify four templates that suffice to describe nearly all classification constraints. These templates effectively capture very common semantic entities in forms and are parametrized using domain knowledge. The building blocks are a domain type (or concept) C and an annotation type A that is used to define a classification constraint for C . None of these templates uses more than one annotation type as template parameter, though many query additional (but fixed) annotation types in their bodies.

Figure 10 shows the classification templates for real-estate and used car: **(1) Concept by proper label.** The first template captures direct classification of a node N with type C , if N matches $x@A\{d,e,p\}$, i.e., has more proper labels of type A than of any other type A' with $A' \prec A$. This template is used by far most frequently, primarily for concepts with unambiguous proper labels. **(2) Concept by segment label.** The second template relaxes the requirement by considering also indirect labels (i.e., labels of the parent segment). In the real estate and used car domains, this template is instantiated primarily for control fields such as ORDER_BY or DISPLAY_METHOD (grid, list, map) where the possible values of the field are often misleading (e.g., an ORDER_BY field may contain “price”, “location”, etc. as values). **(3) Concept by value label.** The third template also considers value labels, but only if neither the first nor the second template can match. In that case, we infer that a field has type C , if the majority of its direct or indirect, value or proper labels are annotated with A . **(4) Min-max concept.** Web forms often show pairs of fields representing min-max values for a feature (e.g., the number of bedrooms of a property). We specify this template with three simple rules (line 5–12), that describe three configurations of segments with fields associated with value labels only (proper labels are captured by the first two templates). It is the only template with two concept template parameters, C and C_M where $C_M \sqsubseteq C$ is the “minmax” variant of C . The first locates, adjacent pairs of such nodes or a single such node and one that is already classified as C . The second rule locates nodes where the second follows directly the first (already classified with C), has a range_connector (e.g., “from” or “to”), and is not annotated with an annotation type with precedence over A . The last rule also locates adjacent pairs of such nodes and classifies them with C_M if they carry a combination of *min* and *max* annotations.

In addition to these templates, there is also a small number of specific rules. In the real estate domain, e.g., we use the following rule to describe forms that use links (a elements) for submission (rather than submit buttons). Identifying such a link (without probing and analysis of Javascript event handlers) is performed based on an annotation type for typical content, title (i.e., tooltip), or alt attribute of contained images. This is mostly, but not entirely domain independent (e.g., in real estate a “rent” link).

```

concept<LINK_BUTTON>(N1)  $\Leftarrow$  form(F), descendant(N1,F), link(N1),
  N1@LINK_BUTTON{d},  $\neg(\text{descendant}(N_2,F),$ 
  (concept<BUTTON>(N2)  $\vee$  follows(N1,N2)))

```

4.3 Model Repair

With fields and segments classified, OPAL verifies and repairs the structure of the form according to structural constraints on the segments, such that it fits to the domain

```

TEMPLATE segment<C>{
2   segment<C>(G) ← outlier<C>(G), child(N1, G), ¬(child(N2, G),
   ¬(C1 → C, concept<C12) ∨ segment<C12))) }
4
TEMPLATE segment_range<C, CM> {
6   segment<C>(G) ← outlier<C>(G), concept<CM1),
   concept<CM2), N1 ≠ N2, child(N1, G), child(N2, G) }
8
TEMPLATE segment_with_unique<C, U> {
10  segment<C>(G) ← outlier<C>(G), child(N1, G), concept<U>(N1, G),
   ¬(C1 → C, child(N2, G), N1 ≠ N2,
12  ¬(concept<C12) ∨ segment<C12))) }
14
TEMPLATE outlier<C>{
   outlier<C>(G) ← child(G, P), child(G', P), ¬(segment<C>(G')) }

```

Fig. 11: OPAL-TL structural constraints

schema. As for classification constraints, we use OPAL-TL to specify the structural constraints. The actual verification and repair is also implemented in OPAL-TL, but since it is not domain independent, it is not exposed to the user for modification. Here, we first introduce typical structural constraints and their templates and then outline the model repair algorithm, but omit the OPAL-TL rules.

Structural constraints. The structural constraints and templates in the real estate and used car domains are shown in Figure 11 (omitting only the instantiation as in the classification case). All segment templates require that there is an outlier among the siblings of the segment: $\text{outlier}\langle C \rangle(G)$ holds if at least one of G 's siblings is not a C segment. (1) *Basic segment.* A segment is a C segment, if its children are only other segments or concepts typed with C . This is the dominant segmentation rules, used, e.g., for `ROOM`, `PRICE`, or `PROPERTY_TYPE` in the real estate domain. (2) *Minmax segment.* A segment is a C segment, if it has at least two field children typed with C_M where $C_M \sqsubset C$ is the minmax type for C . This is used, e.g., for `PRICE` and `BEDROOM` range segments. (3) *Segment with mandatory unique.* A segment is a C segment, if its children are only segments or concepts typed with C except for one (mandatory) field child typed with U where $U \not\sqsubset C$. This is used, e.g., for `GEOGRAPHY` segments where only one `RADIUS` may occur.

Repairing form interpretations. The classification yields a form interpretation F , that is, however, not necessarily a model under Σ , and may contain violations of structural constraints. We adapt the types of fields and segments and the segment hierarchy of F with the rewriting rules described below to construct a form model compliant with Σ . OPAL performs the rewriting in a stratified manner to guarantee termination and introduces at most n new segments where n is the number of fields in the form.

(1) *Under Segmentation:* If there is a segment n with type t such that $\mathcal{C}_{\mathcal{T}}(t)$ requires additional child segments of type $t_1, \dots, t_k \notin \text{child-}\mathcal{T}(n)$, we try to partition the children of n into $k+1$ partitions P_1, \dots, P_k, P_n such that $P_i \models \mathcal{C}_{\mathcal{T}}(t_i)$ and $P_n \cup \{t_1, \dots, t_k\} \models \mathcal{C}_{\mathcal{T}}(t)$. For each P_i we add a new segment node as child of n , classify it with t_i , and move all nodes assigned to P_i from n to that segment. If there is a segment n without type or with type t , but for which $\text{child-}\mathcal{T}(n) \not\models \mathcal{C}_{\mathcal{T}}(t)$ and the above case can not be applied, then that segment may be split: If there are non-overlapping subsequences c_i of children of n , such that all children of n are covered and, for each c_i , there is a type t_i such that the types of c_i satisfy the constraints for t_i , then we replace n with a sequence of segments, one for each c_i typed with t_i .

In practice, few cases of multiple under segmentations occur at the same node and we can limit the search space using a total order on \mathcal{T} . We observe that the number of segments is bounded by the number of fields in the form and provide a pool of unused segments in the segmentation. This avoids the need for value invention in the model repair.

(2) *Over Segmentation:* If there is a segment n of type t with children c_1, \dots, c_k such that $\bigcup \text{child-}\mathcal{T}(c_i) \cup \bigcup_{n' \in C} \tau(n') \models \mathcal{C}_{\mathcal{T}}(t)$ where C is the set of children of n without $c_1 \dots c_k$, then we move the children of each c_i to n and delete all c_i .

(3) *Under Classification:* If there is a segment n of type t with untyped children c_1, \dots, c_k and corresponding types t_1, \dots, t_k such that $\text{child-}\mathcal{T}(n) \cup \{t_1, \dots, t_k\} \models \mathcal{C}_{\mathcal{T}}(t)$ and, for each c_i , $\text{child-}\mathcal{T}(c_i) \models \mathcal{C}_{\mathcal{T}}(t_i)$ holds, then we type c_i with t_i .

(4) *Over Classification:* If there is a segment node n of type t with child c typed t_1 and t_2 such that $\{t_1\} \cup \bigcup_{c' \in C} \tau(c') \models \mathcal{C}_{\mathcal{T}}(t)$ where C is the set of children of n without c , we drop t_2 from $\tau(c)$.

(5) *Miss Classification:* If there is a node n of type t where $\text{child-}\mathcal{T}(n) \not\models \mathcal{C}_{\mathcal{T}}(t)$, then we delete the classification of n as t .

Figure 12 shows the segmentation and classification OPAL obtains for this form before model repair. There are several problems with this segmentation:

(1) The `min_price` and `max_price` fields are not arranged into a range segment as no such node is present in the DOM. This is a case of under segmentation. Following the `segment_range` constraint, OPAL introduces a price range segment to include both fields as in Figure 13a.

(2) The four radio buttons under “order by” are of two different domain types, i.e., `ORDER_BY` for the first two and `display` for the last two. Due to `concept_by_segment` from Figure 10 and the segment label “order by”, the last two would also get classified as `ORDER_BY`, if not for `display < ORDER_BY`. This is an example of the second case of under segmentation, where OPAL needs to split the existing segment as it is not supported by a structural constraint, but there are

Fig. 12: *Farlowestates* before model repair

(a) price range

(b) order-by and display-method

(c) property type

Fig. 13: Model Repair on *Farlowestates* Real Estate Form

subsequences of children that can form valid segments (Figure 13b).

(3) As a result of the original segment with four radio buttons grouped together, the last two radio buttons in the four are also typed as `ORDER_BY` in addition to their `display` type. OPAL resolves this over classification by removing the `ORDER_BY` following the restructuring of the segment.

(4) The `PROPERTY_TYPE` segment is subdivided into two segments in the original segmentation, since OPAL identifies no style-equivalence among the six checkboxes due to lack of similarity. However, two segments of `PROPERTY_TYPE` can not be contained in a single parent segment (due to outlier). Thus, the two segments are removed with all their children directly contained in the larger segment (Figure 13c). This is an example of over segmentation.

(5) The segmentation obtained at segment scope preserves the two DOM nodes representing two form rows. However, in the domain schema, these nodes do not carry meaning, and thus are treated as over segmentation and removed.

4.4 Domain Instantiation: Methodology and Example

In this section, we demonstrate how to derive an OPAL domain schema, which includes form specific concepts, from a given standard ontology of a domain. This is the typical way to instantiate a domain for use with OPAL.

Figure 14 shows a simple ontology for the used car domain (in the UK). Note, that most search forms are about searching for entities (double border in Figure 14) by their properties (single border) such as price or mileage of a car. Therefore, most of the types in an OPAL domain schema correspond to such properties of entities in the domain.

We observe that properties can be roughly distinguished into numerical, categorical, and free text according to their range and that these distinctions dictate to a large extent the expected form fields for searching by those properties. For a numerical property we expect, e.g., either a single text input or slider, two min-max fields for entering a range, or a set of checkboxes to select common values or ranges. Categorical properties, on the other hand, never exhibit range inputs.

These observations are codified in the derivation templates of Figure 15. These templates group typical instantiations for the above kinds of properties as well as for compound object types such as `LOCATION` in Figure 14:

(1) For an **object type** (`ENGINE`), we instantiate only the `segment<C>` template, i.e., we allow segments, but not fields of this type. Such segments typically collect multiple properties of the object type, e.g., `ENGINE_SIZE` and `FUEL_TYPE`.

(2) For a **free text type** (e.g., `ADDRESS`), we instantiate only the `concept_by_proper<C,A>` and `concept_by_value<C,A>` templates that allows fields, but not segments of that type. There is usually no need for a segment in this case, as there are rarely multiple occurrences of fields for such a type. In the rare case where that is nevertheless possible, we instantiate `segment<C>` separately.

(3) For a **categorical type** (`MAKE` or `COLOUR`), we instantiate in addition to `concept_by_proper<C,A>` also `segment<C>` and the `concept_by_segment<C,A>`. Categorical types are often represented as single select boxes or lists of radio buttons or check boxes. For the latter, an enclosing segment is desir-

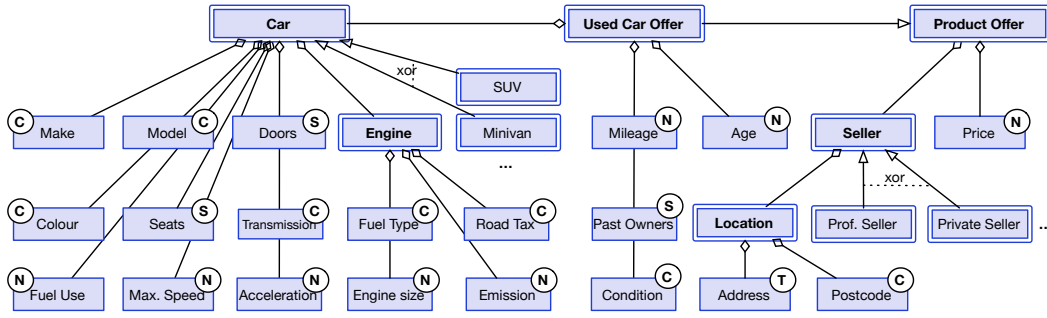


Fig. 14: Used car ontology

```

1  TEMPLATE object_type<C> {
2    INSTANTIATE segment<C> using { <C> } }

4  TEMPLATE free_text_type<C,A> {
5    INSTANTIATE concept_by_proper<C,A> using { <C,A> }
6    INSTANTIATE concept_by_value<C,A> using { <C,A> } }

8  TEMPLATE categorical_type<C,A> {
9    INSTANTIATE concept_by_proper<C,A> using { <C,A> }
10   INSTANTIATE concept_by_segment<C,A> using { <C,A> }
11   INSTANTIATE concept_by_value<C,A> using { <C,A> }
12   INSTANTIATE segment<C> using { <C> } }

14 TEMPLATE numeric_type<C,C_M, A> {
15   INSTANTIATE concept_by_proper<C,A> using { <C,A> }
16   INSTANTIATE concept_by_segment<C,A> using { <C,A> }
17   INSTANTIATE concept_by_value<C,A> using { <C,A> }
18   INSTANTIATE concept_minmax<C,C_M,A> using { <C,C_M,A> }
19   INSTANTIATE segment<C> using { <C> }
20   INSTANTIATE segment_range<C,C_M> using { <C,C_M> } }

```

Fig. 15: Template for different property kinds

able and `concept_by_segment<C,A>` allows us to propagate the segment labels to the fields.

(4) For a **numerical type** (PRICE or seats), we also instantiate the `segment_range` and `concept_minmax` templates, enabling the classification of range segments and fields.

With these templates, we can derive an OPAL annotation and domain schema very quickly from a given domain schema such as Figure 14.

First, we normalize the ontology: If a class C has sub-classes without additional properties (type classes), we generate a new categorical property C_TYPE , add all labels from the sub-classes to that property, and remove the sub-classes.

Second, we derive the annotation schema and, in particular, the necessary annotators as follows:

(1) For each concept or property c of the ontology, we create an annotation type c . All *labels* of c , possibly enriched with synonyms from an external knowledge base such as Wordnet, form an annotator for the proper labels of the concept ($isLabel_c$).

(2) For categorical concepts or properties, we require a given list of instances, an existing annotator, or another entity recogniser, again possibly provided by an external knowledge base such as DBpedia or LinkedGeoData. Numerical values are treated similarly, though these often take simply the form of number in a certain range. This provides $isValue_c$.

Third, we derive the domain schema in four steps:

(1) For each **class** C , add an instantiation rule for `object_type<C>`. In our example, this yields 6 instantiations (recall, that type classes are normalised to properties above).

(2) For each **property**, add an instantiation rule of corresponding type, e.g.,

```
INSTANTIATE numeric_type<C,C_M,A> using {<PRICE, PRICE_M, price>}
```

In our example, this yields 22 instantiations (20 properties from Figure 14 and two `..._type` properties).

(3) Determine which “presentational” fields and segments occur in the given domain and add them to the domain schema. A field or segment is presentational, if it determines the way the results are represented. In the used car and real estate domains, we identify two types of presentational fields: “order-by” and “pagination” which control the order in which the results are presented as well as the number of results per page. These presentational types are mostly shared between domains and can be easily reused thanks to OPAL-TL templates:

```
INSTANTIATE categorical_type<C, A> using
{ <ORDER_BY, order_by> <PAGINATION, pagination> }
```

In this step, we also add generic rules that are independent of the domain, e.g., for the form itself and domain-independent form facilities such as submit buttons or generic keyword search fields.

(4) Sometimes small manual adjustments are necessary. For example, numerical types may occur with multiple units of measure or other modifiers, e.g., prices with different currencies or locations with a search radius. Such modifier fields are usually unique in their corresponding segment and thus added using the `segment_with_unique<C,U>` template. In

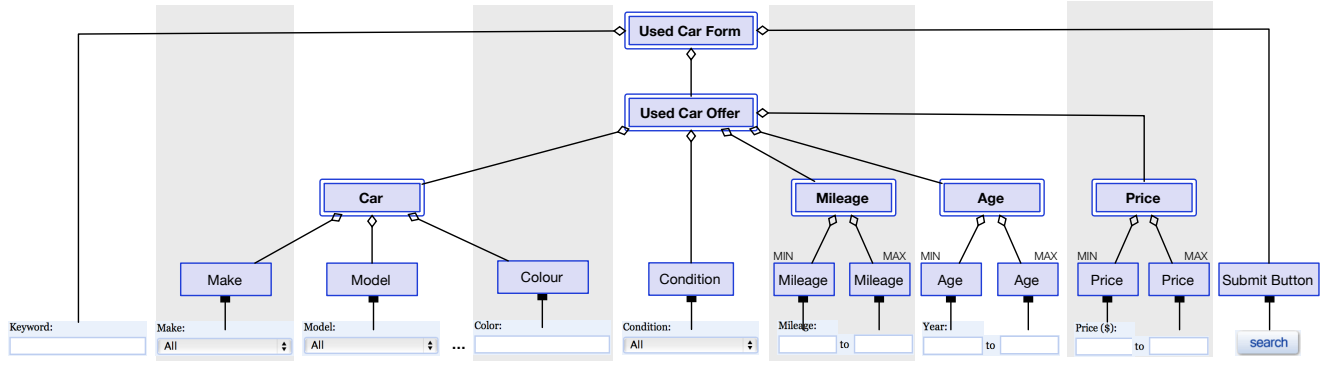


Fig. 16: Used car: classified form

the used car domain, we can observe this for `CURRENCY` and `RADIUS`:

```

INstantiate TEMPLATE segment_with_unique<C,U> using
{ <PRICE, CURRENCY> <LOCATION, RADIUS> }
INstantiate TEMPLATE concept_by_proper<C,A> using
{ <CURRENCY, currency>, <RADIUS, radius> }
INstantiate TEMPLATE concept_by_value<C,A> using
{ <CURRENCY, currency>, <RADIUS, radius> }

```

Some object types, in particular `LOCATION`, may also be entered as a whole through free text fields and accordingly instantiate the `free_text_type` template for them:

```

INstantiate TEMPLATE free_text_type<C,A> using
{ <LOCATION, location> }

```

Finally, we need to determine part-of and precedence between types. The part-of relation is derived from the associations of the domain schema, e.g., `ADDRESS` \rightarrow `LOCATION`, `POSTCODE` \rightarrow `LOCATION`, `FUEL_TYPE` \rightarrow `ENGINE` for our case. Precedence requires some observation of cases where annotations for different types overlap. Typically, we want to give presentational types precedence over all domain types (as they often contain values such as “sort by price”). For the used car domain, we observe that `PAGINATION` \prec `ORDER_BY` and that both have precedence over all domain types. We also observe that `MILEAGE` and `RADIUS` (in locations) can have overlapping values. Though `radius` is only used in `segment_with_unique<C,U>`, for `LOCATION` segments which disallow `MILEAGE` elements, we add `MILEAGE` \prec `RADIUS` to express a bias for `MILEAGE`.

Figure 16 shows a form from the used car domain fully classified according to this domain schema.

5 Light-weight Form Integration

OPAL’s form models allow the easy implementation of many types of applications that require automatic understanding and interaction with forms, such as form integration and filling, data extraction, or web automation. As discussed in Section 2, we focus here on *form integration* (or filling), i.e., the

part of a web integration system [14] that translates a query on the global schema (OPAL’s domain schema) to a query against concrete forms. In this section, we introduce a light-weight form integration system that performs this task fully automatically for thousands of forms in a domain, given only an OPAL domain schema. We have instantiated this system for the real estate and used car domain, but OPAL is as easily applied to other domains, since only a very limited amount of additional customisation is needed (on type variations and, possibly, similarities).

Recall, that we focus on the optimistic, single-query variant of the form integration problem: We aim for a single-query that returns all results matching the global (or *master*) query, but allow to return also non-matching results, if there is no more specific query that returns all matching ones.

OPAL’s form integration translates the master query into concrete queries through a small set of translation rules supported by a notion of similarity on property values. OPAL can perform form integration without any other information than what is provided by an OPAL domain schema and corresponding form model. However, it can be further improved by providing additional domain-specific information.

Similarity on values is represented as a real-valued function on pairs of values and is based on the property type: For free-text and categorical properties, OPAL uses a mix of Levenshtein and longest common substring distance, for numeric properties a difference-based similarity. A domain schema can be enhanced by property-specific similarity function, e.g., to deal with different units of measure. A small set of such functions is provided with OPAL: for price, for distance properties, and for dates.

Translation rules use these similarity functions to translate the constraints of the master query Q into queries on the concrete forms. For each form F with form model M and constraint $C \in Q$ on type T , we retrieve the fields f_1, \dots, f_n classified with T . Let $\text{values}(C)$ be the (possibly infinite) set of values for which C holds.

- (1) *Single field, single value:* If $n = 1$, $\text{values}(C) = \{v\}$, and
 - (i) f_1 is a free text input, return $f_1 = v$.

- (ii) f_1 is a select box, return $f_1 = v'$ where v' is the option of f_1 most similar to v .
- (2) *Multi field*: If $n \geq 1$,
 - (i) $\text{values}(C) = \{v\}$, and all f_i are radio buttons (exclusive options), return $f_k = \text{true}$ for the f_k that is most similar to v .
 - (ii) $\text{values}(C) = \{v_1, \dots, v_k\}$ and all f_i are check boxes (non-exclusive options), return $f_k = \text{true}$ for each f_k where a v_i exists such that the similarity of f_k and v_i is minimal among all such pairs.
 - (iii) and all f_i are free-text range input fields (i.e., of type T_M , where T_M is the minmax type to T), then return $f_s = v_1$ for each f_s that is a minimum input and $f_e = v_k$ for each f_k that is a maximum input.
 - (iv) and all f_i are select-box range input fields, then return $f_s = v'_1$ for each f_s that is a minimum input where v'_1 is the most similar option of f_s to v_i that is smaller or equal to v_1 . Analog for f_e .

In all other cases (e.g., a select box for a set inclusion constraint), we return no constraints to avoid false negatives.

In many domains, we can observe that the same information is represented in alternative ways on different sites. E.g., the age of a car is represented by the manufacturing year on same sites. Similarly, the location of property may be given as a street address, a postcode, or even just a town, in particular for rural agencies. To treat this cases, we need to be able to translate a constraint such as “AGE = 6” to a constraint “YEAR = 2006” or “POSTCODE = OX1” to “TOWN = Oxford”. We call AGE and YEAR *type variants* and amend the domain schema with a value mapping for each pair of type variants. Value mappings for numerical properties are typically simple conversion functions, e.g., from different units of measure. Value mappings for categorical properties are typically realised by a query to an external database or service such as DBpedia. In our example domains, we use value mappings for conversions of metric and imperial distances as well as of postcodes to towns and other locations. To treat type variants we perform the following test and translation before the aforementioned translation rules:

- (0) *Type variants*. If $n = 0$ and there is a field f' with type T' such that T' is a variant type of T , we translate the values in C to T' and continue with that constraint.

With those simple rules, OPAL’s form integration manages to translate most constraints as shown in Section 6. There are, of course, still cases where the translation fails, e.g., if categorical values are mapped to ranges by some ordering such as road tax brackets or iPhone models (ordered according to year of introduction). But as demonstrated in Section 6, this light-weight simple form integration already provides us with a successful translation of a master query in the vast majority of cases.

To illustrate OPAL’s form integration, we consider the form of [primelocation.com](http://www.primelocation.com) as shown in the middle of Fig-

The screenshot shows the OPAL Testing Tool interface overlaid on a web browser displaying the Primelocation.com website. The tool's interface includes a top navigation bar with links like 'Find A Property For Sale', 'Houses & Flats To Buy', and 'Primelocation'. Below this, there's a search bar with a 'search' button. The main content area shows a form for finding property for sale, with fields for 'Location' (set to 'London'), 'price range' (set to '£70,000' to '£190,000'), 'property type' (set to 'House & Flat'), and 'min bedrooms' (set to '3'). The tool highlights various form elements with colored boxes: a green box for the 'price range' label, a blue box for the 'minimum' label, a red box for the 'maximum' label, and a yellow box for the 'min bedrooms' label. The tool also shows a 'Domain Value' section at the bottom with a dropdown for 'domain' (set to 'UK real estate') and input fields for 'min price (GBP)' (75000) and 'max price (GBP)' (185000). A 'Confirm' button is at the bottom right.

Fig. 17: OPAL Testing Tool

ure 17. The figure shows the OPAL testing tool that we use to test and verify the accuracy of OPAL domain schemas. It allows the user to visualize the form labels, form segments, and classifications derived by OPAL and to track down, where, e.g., there are problems with the classification constraints or the annotations. It also provides a master query in the lower third. The concrete form is automatically filled according to the values provided in the master form. This allows the user to visually verify that the query has been translated correctly. The master form is automatically generated from the domain schema, but the user can provide additional information on which fields to include. For space reasons, we have focused in Figure 17 on the types most commonly used in constraints in the UK real estate domain.

For the concrete form from [primelocation.com](http://www.primelocation.com), we highlight form fields and labels by colouring them with the same color (here, e.g., the “minimum” and the first price field). Form segments are shown as boxes with no filling except for their labels (a price segment with “price range” label). The figure shows the form *after* OPAL has filled it according to the values from the master query. Notice, how for the three select boxes for minimum and maximum price, as well as bedroom number, OPAL picks the closest value to the one specified in the master form.

6 Evaluation

We perform experiments on several domains across four different datasets. Two datasets are randomly sampled from the UK real estate and UK used-car domains, respectively. We compare with existing approaches via ICQ and TEL-8, two

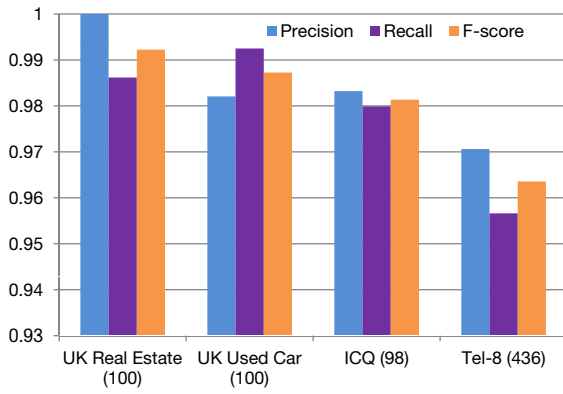


Fig. 18: OPAL on 734 forms

public benchmark sets, on which we only evaluate OPAL’s form labeling. This limitation necessary to allow a comparison that is fair to existing approaches, that only label forms and do not use domain knowledge. Even with this limitation, however, OPAL outperforms previous approaches in most domains by at least 5%. We also perform an introspective analysis of OPAL to show (1) the impact of field, segment, layout, and repair in the form interpretation, (2) OPAL’s performance and scalability with increasing page size, and (3) the effectiveness of the form integration in OPAL.

We evaluate the proper assignment of text nodes to form fields using standard notions of precision, recall and F-score (harmonic mean $F = F_1 = 2PR/(P+R)$ of precision and recall). For form labeling (classification), precision P is measured as the proportion of correctly labeled (classified) fields over total labeled fields, while recall R is the fraction of correctly labeled fields over total number of fields. For form filling precision and recall do not apply and we therefore report the error rate as portion of total fields that are not correctly filled (i.e., either filled but with a wrong value or not filled at all, despite a corresponding constraint in the master query). For all considered datasets, we compare the extracted result to a manually constructed gold standard. We evaluate segmentation through their impact on classification, see Figure 22, and the improved performance on the two datasets where we perform form interpretation (UK real estate and used car) versus the ICQ and TEL-8 datasets.

Datasets. For the UK real estate domain, we build a dataset randomly selecting 100 real estate agents from the UK yellow pages (yellow.com). Similarly, we randomly pick 100 used-car dealers from the UK largest aggregator website autotrader.co.uk. The forms in these two domains have significantly different characteristics than the ones in ICQ and TEL-8, mainly due to changes in web technology and web design practices. The usage of CSS stylesheets for layout and AJAX features are among the most relevant.

The ICQ and TEL-8 datasets cover several domains. ICQ presents forms from five domains: air traveling, (used) cars, books, jobs, (U.S.) real estate. There are 20 web pages for each of the domains, but two of them are no longer accessible and thus excluded from this evaluation. TEL-8, on the other hand, contains forms from eight domains: books, car rental, jobs, hotels, airlines, auto, movies and music records. The dataset amounts to 477 forms, but only 436 of them are accessible (even in the cached version).

6.1 Field Labeling

In our first experiment we evaluate the accuracy of OPAL’s field labeling on all four datasets, but only in the UK real estate and used car domain we employ the form interpretation to further improve the field labeling. Figure 18 shows the results. The first two bars are for the random sample datasets. For the real estate domain, OPAL classifies fields with perfect precision and 98.6% recall. Overall we obtain a remarkable 99.2% F-score. The result is similar for the used car domain, where OPAL obtain 98.2% precision and 99.2% recall, that amount to 98.7% F-score. OPAL achieves lower precision than recall in the used car domain due to the fact that web forms in this domain are more interactive: certain fields are enabled only when some other field is filled properly, yet non-field placeholders are present in the HTML to indicate that a field will appear when the other field is filled. This introduces noise to field labeling and thus classification.

For the real estate domain, our domain schema consists of a few dozen field and segment types and about 40 annotation types. Similarly, in the used car domain, there are about 30 annotation types. Creating an initial domain schema (including gazetteers and testing) takes a single person familiar with a domain and OPAL-TL roughly 1 week.

The other two entries in Figure 18 regard field labeling on ICQ and TEL-8 datasets. On these, OPAL applies only its domain-independent scopes (field, segment, scope) as no domain schema is available for these domains. Nonetheless, OPAL reports very high accuracy also on these forms, confirming the effectiveness of our domain-independent analysis. Not unexpected, OPAL performs better in the UK real estate and used car domain where domain knowledge is present, even though the forms in those datasets are on average more modern and contain more fields (10.4 and 9.2 fields per form in the real-estate and used-car dataset versus 6.5 and 7.9 fields per form for ICQ and Tel-8).

Cross Domain Comparison. We use ICQ and TEL-8 to compare field labeling in OPAL against existing approaches, on a wide set of domains. Figure 19a details the result of OPAL on each domain of the ICQ dataset. It shows perfect F-score values for the jobs domain (100%) as well as auto and air travelling (99.3% and 98.3%). For comparison, [10]

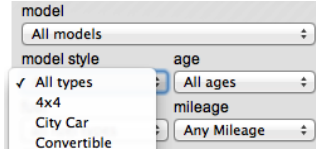


Fig. 21: Classification error example

6.2 Form Interpretation

The quality of OPAL’s form interpretation depends on the quality of the form labeling and that of the annotators. As discussed above, for this evaluation we use annotators that have been created in about 1 week for the UK real estate and used car domain. The location related annotators are based on standard sources (GeoNames and LinkedGeoData) and thus have reasonable recall, but precision is fairly low, due to the high number of locations in the UK that are homonyms to common English words (e.g., the town of “Selling”). Such noise in the value annotators, however, affects OPAL very little, as the values of form fields are only used if the labels are inconclusive and we only use the most frequent annotation type. Noise in the label values is far more likely to lead to classification errors. However, typical annotators are small lists of 5 – 10 typical labels which are easy to create and have very low noise. E.g., for *bedroom* labels we use just “bedroom”, “bed”, and their plural forms, for *make*, *model*, *mileage* and many more just “make”, “model”, “mileage”, and their plural form, resp.

With this, we achieve near perfect classification, correctly classifying most of the fields, see Table 1: Precision is 97.3% over all fields in the real estate data set (with just 24 out of 931 classified fields incorrectly classified) and recall 97.4%. This excludes 56 (or 5.5%) fields for which our domain schema does not contain a concept (usually as they appear only very rarely).

Classification errors are mostly caused by ambiguity in the used form labels. For example, Figure 21 shows a form, where the “model style” field is erroneously classified as a *MODEL* field by OPAL. The field has a proper label “model style” which is correctly assigned to the field in the field labeling, as are the field values “4x4”, “City Car”, etc. In the classification, we prioritise proper labels over values (as value annotators are more noisy). In most cases, this is indeed preferable, but here the proper label “model style” is annotated with *model* and we classify the field as *model* rather than *car_type*, as “model style” is not recognised as a label for *car_type*. A probabilistic classifications that combines classifications from labels and values (with a lower weight) would allow us to choose the most likely global form classification and thus to address such outliers. However, this would also increase the effort in creating a domain schema.

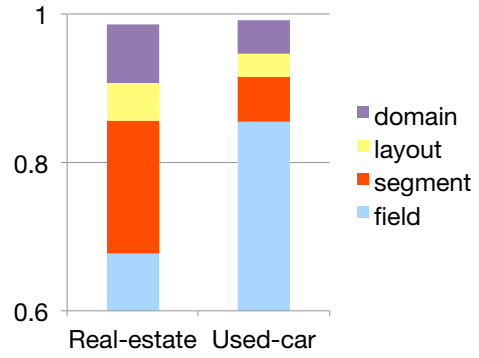


Fig. 22: Scopes

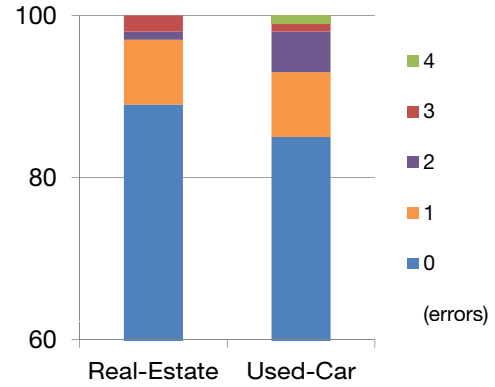


Fig. 23: Form integration errors (per form)

6.3 Contributions of Scopes

We demonstrate the effectiveness of combining different types of analysis by measuring to what extent each of our four scopes contributes to the overall quality of form understanding. We use again the two domain datasets from the previous experiment. For both we show the results for recall, though the picture is similar for precision and F-score, cf. Figure 18. As illustrated in Figure 22, for the field labeling in the real-estate dataset, the field scope already contributes significantly (67%). The Segment scope increases recall by 18%, layout scope and the repair in the form interpretation add together another 13%. Note that, the contribution of the repair in the form interpretation is more significant than that of the layout scope, indicating the importance of domain knowledge to achieve very high accuracy form understanding. In the used car domain, field scope alone is even more significant 85% (as many of the websites use modern web technologies and frameworks with reasonable structure).

6.4 Form Integration

For the evaluation of the form integration, we determine the error rate in the query translation for all forms in the used

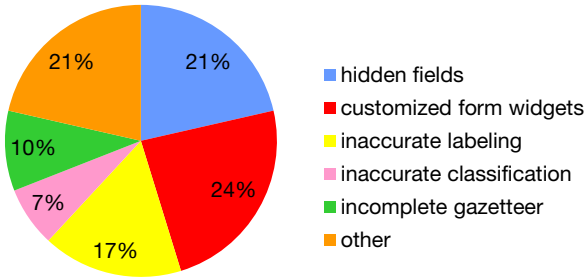


Fig. 24: Types and distribution of form integration errors

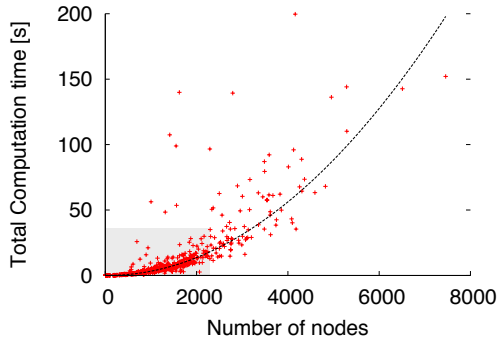


Fig. 25: Time

car and real estate datasets. We use multiple master queries in both cases, using for the real estate domain combinations of location, min price, max price, and min bedroom. For the used car domain, we use combinations of location, make, model, min price, and max price. We evaluate the constraints separately and consider a constraint correctly translated, if it involves the right field on the concrete form and uses the best matching value. Overall, OPAL generates 95.6% and 93.8% correctly translated constraints.

Figure 23 presents the number of web forms where OPAL fails to translate one or more constraints incorrectly. Overall, 87% of the forms were filled perfectly, and 95% of the forms have no more than one failure. Figure 24 presents the major causes for OPAL’s failure in translating constraints: Most of the errors are caused by scripted forms with hidden (21%) or heavily customised form controls (24%). The remaining cases divide rather evenly between errors in the form labeling (17%), in the classification or annotation (incomplete gazetteer), and an assortment of other issues, mostly browser related (e.g., scripted popovers that block access to the form fields or fields that can only be filled in a certain order).

6.5 Scalability

As discussed in Sections 3 and 4, overall the analysis of OPAL is bounded by $O(n^2)$ due to the layout scope. As expected actual performance follows a quadratic curve, but

with very low constants. There is a significant amount of outliers, partially due to long page rendering time and partially due to variance in the depth and sophistication of the HTML structure. Figure 25 reports OPAL performance on all 534 forms in the combined TEL-8 and ICQ datasets. The highlight area covers 80% of the forms with 2200 nodes. OPAL requires at most 30s for the analysis (including page rendering) of these forms. Further analysis on the effect of increasing field or form numbers confirms that these have little effect and page size is the dominant factor.

7 Related Work

Form understanding has attracted a number of approaches motivated by deep web search [20,27,28], meta-search engines and web form integration [15,10,31,32,33,35] and web extraction [29,30]. We focus here on differences to OPAL, for a complete survey see [18,11]. We present related work for form understanding and form integration separately, as not all approaches consider both aspects.

7.1 Form Understanding

Form understanding approaches can be roughly categorised by the fundamental approach to the problem:

(1) The most common type encodes (mostly domain independent) observations on typical forms into implicit heuristics or explicit rules MetaQuerier [35], ExQ [32], SchemaTree [10], LITE [27], Wise-i-Extractor [15], DEQUE [28], and CombMatch [16]. (2) Alternatively, some approaches LabelEx [23] and HMM [17] use machine learning from a set of example forms (possibly of a specific domain). (3) Form understanding is often done to surface the results hidden behind the form and approaches such as [20,31,27] exploit the extracted results for form understanding.

Aside of system design, OPAL primarily differs from these approaches in two aspects: (1) They mostly incorporate only one or two of OPAL’s scopes (and feature classes): MetaQuerier, ExQ, and SchemaTree mostly ignore the HTML structure (and thus field and segmentation scope) and rely on visual heuristics only; CombMatch, LITE, DEQUE, and LabelEx ignore field grouping. HMM ignores visual information. [20,31,27] use only the HTML structure, but exploit probing information, i.e., whether a submission is successful or not. (2) None of the approaches provides a proper form model classifying the form fields according to a given schema. Furthermore, no approach uses domain knowledge is used to improve the labeling or verify the classification, though LabelEx analyses domain specific term frequencies of label texts and HMM checks for generic terms, such as “min”. As evident in our evaluation, each of the scopes in OPAL considerably affects the quality of the form labeling and classifi-

cation. The fact, that each of these approaches omits at least one of the domain-independent scopes, explains the significant advantage in accuracy OPAL exhibits on Tel-8 and ICQ. Notice also that not using domain knowledge keeps these approaches out of reach of the nearly perfect field classification achieved by OPAL.

Form understanding by observation and heuristics. Most closely related in spirit to OPAL, though very different in realisation and accuracy, is MetaQuerier [35]. It is built upon the assumption that web forms follow a “hidden syntax” which is implicitly codified in common web design rules. To uncover this hidden syntax, MetaQuerier treats form understanding as a parsing problem, interpreting the page a sequence of “atomic visual elements”, each coming with a number of attributes, in particular with its bounding box. In a study covering 150 forms, the authors of MetaQuerier identified 21 common design patterns. These patterns are captured by production rules in grammar with preferences. Metaquerier is not parameterisable for a specific domain. In contrast, the domain independent part of OPAL achieves nearly perfect accuracy with only 6 generic patterns by combining visual, structural, and textual features, and a simple prioritisation of these patterns by scope. OPAL’s domain dependent part allows us to adjust it for patterns specific to a domain.

ExQ [32] is similarly based primarily on visual features such as a bias for the top-left located labels comparable to OPAL, but disregards most structural clues, such as explicit for attributes of label tags and does not allow for any domain specific patterns.

Also SchemaTree [10] uses only visual features (and the tabindex and for attributes for fields and labels). It exploits nine observations on form design, e.g., that query interfaces are organised top-down and left-to-right or that fields form semantic groups. It uses a hierarchical alignment between fields and text nodes similar to OPAL’s segment scope and a “schema tree” where the nine observations are observed. Again, no adaptation to a specific domain is possible.

Wise-iExtractor [15] firstly tokenizes the form to obtain a high-level visual layout description (an *interface expressions (IEXP)*), distinguishing text fragments, form fields, and delimiters, such as line breaks. It then associates texts and fields by computing the *association weight* between any given field and the texts in the same line and the two preceding lines, exploiting ending colons, similarities between the text and the field’s HTML name attribute, and the text-field distance. In addition, Wise also identifies generic relationships between fields: range (e.g. from, to), part (e.g. first and last name), group (e.g. radio buttons), or constraint (e.g. exact match required). However, in contrast to OPAL their form labeling only explores limited visual and textual information relying mainly on weight computation. Moreover, their domain-independent typing shares some similar-

ities with OPAL’s templates but lacks the flexibility provided by OPAL’s domain schemata that allow us to adjust these generic types to a given domain. Though these adjustments are often small, their impact is significant, as shown in Section 6.

In [34], a (manually derived) domain schema is used to guide understanding. In contrast to OPAL, it segments a form purely based on the domain schema (called schema tree). They evaluate on a fragment (around 100-150 forms) of TEL-8 using domain schemata derived from the rest of TEL-8 (about 250 forms). This yields on the considered fragment similar accuracy as OPAL achieves on the full TEL-8, yet OPAL does not use any domain schema in this case, let alone domain schemata specifically trained on TEL-8.

Form understanding by learning from example forms.

Where the above approaches rely on humans to derive heuristics and rules for form understanding, the following approaches use machine learning on a set of example forms. Therefore, they can also be trivially adapted to a specific domain by using domain-specific training data. The evaluation in [17], however, shows little effect of domain-specific training data: a training set from the biological domain outperforms domain-specific training set in four out of five other domains.

LabelEx [23] uses limited domain knowledge when considering the occurrence frequencies of label terms. Domain relevance of the terms occurring in a label, measured as the occurrence frequency in previous forms, is one feature used to score field-label candidates. Field-label candidates are otherwise created primarily using neighbourhood and other visual features, as well as their HTML markup. However, LabelEx does not consider field groups and thus is unable to describe segments of semantically related fields or to align fields and labels based on the group structure and does not use any domain knowledge aside of term frequency.

HMM [17] uses predefined knowledge on typical terms in forms, such as “between”, “min”, or “max”, but does not adapt these for a specific domain. HMM employs two hidden Markov models to model an “artificial web designer”. During form analysis, the HMMs are used to explain the phenomena observed on the page: The state sequences, that are most likely to produce the given web form, are considered explanations of the form. Compared to OPAL, HMM uses no visual features and no domain knowledge.

Form understanding by probing. All the above approaches conduct their analysis based purely on information available on the web forms. Alternatively, there is also an indirect route for form understanding by submitting the forms and analysing the query results, which often are much easier to classify (as there are many instances compared to a single form). The price is, however, that a certain amount of

analysis of those result pages is necessary. Therefore, this is primarily used in a context where such analysis is anyway required, e.g., in crawlers or data extraction systems. Typically, these approaches use an incremental approach, identifying inputs for some fields, submitting the form, analysing the result page, and then possibly restarting the whole process, now with, e.g., an increased set of input values for the form. For example, [20] determines whether a field must be filled or is a “free” input by iterating over possible templates and selecting those that return sufficiently distinct result pages. This is driven by the desire to surface some representative, but not necessarily complete set of results from the web form. None of these approaches produces a sophisticated form model, but at best rough classifications of the fields and whether they are mandatory.

7.2 Form Filling and Integration

Form integration has been considered in many shapes, either as “meta-search” where a master query on a given global schema is translated to concrete forms as in OPAL, as “interface matching” where many concrete forms are integrated without a global schema (often using schema matching), or as “query generation” in the context of data extraction or crawling where the aim is to generate a set of queries to extract all or most of the data, but often not even full form understanding is performed.

Though some query generation and most interface matching approaches use form understanding, they are focused on different issues than OPAL’s form integration which is a type of “meta-search”: How to find an optimal query set that uncovers as much deep content as possible [3], how to determine if a query will produce relevant data even if only partial information about the data is available [5], how to maximize the diversity of the extracted content [20], or how to identify semantic equivalences between fields from different forms [24].

Similar to OPAL, [1] fills web forms by connecting fields at the conceptual level, but with WordNet [26] instead of proper annotations. Furthermore, OPAL produces more structured form model that is verified against a domain schema. Metaquerier [9], targets the integration of web sources and tackles query translation for form filling in that context. As OPAL, Metaquerier selects values closest to the constraint in the source query (similar to our master query). They also perform type-based query translation to map a source query to a target query considering numeric and text types, but achieve only 87% accuracy. OPAL performs form filling in a similar fashion, but also considers the number of fields for each domain type in the master query and performs significantly better (93%).

8 Conclusion and Future Work

To the best of our knowledge, OPAL is the first comprehensive approach to form understanding and integration. Previous form understanding approaches has been limited mainly by overly generic, domain independent, monolithic algorithms relying on narrow feature sets. OPAL pushes the state of the art significantly, addressing these limitations through a very accurate domain independent form labeling, exploiting visual, textual, and structural features, by itself already outperforming existing approaches. This domain independent part is complemented with a domain dependent form field classification that significantly improves the overall quality of the form understanding and produces nearly perfect form interpretations. Accurate form interpretations enables form integration: OPAL successfully realizes a lightweight form integration system, able to translate master queries to forms of a domain with nearly no errors.

Nevertheless, there remain open issues in OPAL and form understanding in general that need to be addressed for form understanding to become a reliable tool to access web data through forms with little more effort than through APIs:

(1) Dynamic, scripted forms: OPAL is able to understand most static forms with near perfect accuracy, but performs much worse on dynamic forms. We are already working on an extension of OPAL for dealing with dynamic, heavily scripted interfaces that combines ideas from state exploration and crawling with form understanding.

(2) Customised form widgets: More and more forms use customised widgets such as tree views or sliders. Though most of these cases use hidden form fields that can be analysed by OPAL, the use of fully scripted cases increases. We plan to extend OPAL to allow the customisation of the form widgets that it can recognise. However, if these cases become more common, it may become necessary to automatically explore and learn such new widget types.

(3) Probing-based understanding: One of OPAL’s virtues is that it achieves its near perfect accuracy without any probing, but thus from the form page alone. However, this also limits the information that OPAL can provide, and prevents the verification and repair of the form model through the results returned by a form submission. For applications that need to access the result pages (e.g., data extraction and surfacing), we plan to integrate OPAL with the result page analysis system AMBER [13] to further improve accuracy and to address integrity and access constraints.

(4) Integrity and access constraints. OPAL produces some integrity constraints through the domain schema and its form segmentation, e.g., dependencies between min and max fields in a range segment. We see an increase in the use of integrity constraints in forms thanks to the availability of easy-to-use client-side validation libraries. Lightweight methods for analysing and exploiting such client side vali-

dation would allow us to extend our form models with more detailed integrity constraints. This is in addition to integrity and access constraints derived from probing.

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References

1. S. Araujo, Q. Gao, E. Leonardi, and G.-J. Houben. Carbon: domain-independent automatic web form filling. In *Proc. Int'l. Conf. on Web Engineering (ICWE)*, pages 292–306, 2010.
2. Z. Bar-Yossef and M. Gurevich. Random sampling from a search engine's index. *J. ACM*, 55(5):24:1–24:74, 2008.
3. L. Barbosa and J. Freire. Siphoning hidden-web data through keyword-based interfaces. In *Proc. Brazilian Symp. on Database*, pages 309–321, 2004.
4. L. Barbosa and J. Freire. Combining classifiers to identify online databases. In *Proc. Int'l. World Wide Web Conf. (WWW)*, pages 431–440, 2007.
5. M. Benedikt, G. Gottlob, and P. Senellart. Determining relevance of accesses at runtime. In *Proc. Symp. on Principles of Database Systems (PODS)*, pages 211–222, 2011.
6. M. Benedikt and C. Koch. XPath leashed. *ACM Computing Surveys*, pages 3:1–3:54, 2007.
7. A. Bilke and F. Naumann. Schema matching using duplicates. In *Proc. Int'l. Conf. on Data Engineering (ICDE)*, pages 69–80, 2005.
8. M. J. Cafarella, E. Y. Chang, A. Fikes, A. Y. Halevy, W. C. Hsieh, A. Lerner, J. Madhavan, and S. Muthukrishnan. Data management projects at google. *Sigmod Records*, 37(1):34–38, 2008.
9. K. C.-C. Chang, B. He, and Z. Zhang. Mining semantics for large scale integration on the web: evidences, insights, and challenges. *SIGKDD Explor. Newsl.*, 6(2):67–76, Dec. 2004.
10. E. C. Dragut, T. Kabisch, C. Yu, and U. Leser. A hierarchical approach to model web query interfaces for web source integration. In *Proc. Int'l. Conf. on Very Large Data Bases (VLDB)*, pages 325–336, 2009.
11. E. C. Dragut, W. Meng, and C. T. Yu. *Deep Web Query Interface Understanding and Integration*. Synthesis Lectures on Data Management. Morgan & Claypool Publishers, 2012.
12. T. Furche, G. Gottlob, G. Grasso, X. Guo, G. Orsi, and C. Schallhart. Opal: automated form understanding for the deep web. In *Proc. Int'l. World Wide Web Conf. (WWW)*, pages 829–838, 2012.
13. T. Furche, G. Gottlob, G. Grasso, G. Orsi, C. Schallhart, and C. Wang. Little Knowledge Rules The Web: Domain-Centric Result Page Extraction. In *Proc. Int'l. Conf. on Web Reasoning and Rule Systems (RR)*, pages 61–76, 2011.
14. B. He, Z. Zhang, and K. C.-C. Chang. Towards building a meta-querier: Extracting and matching web query interfaces. In *Proc. Int'l. Conf. on Data Engineering (ICDE)*, pages 1098–1099, 2005.
15. H. He, W. Meng, Y. Lu, C. Yu, and Z. Zhang. Towards deeper understanding of the search interfaces of the deep web. *World Wide Web*, 10:133–155, 2007.
16. O. Kaljuvee, O. Buyukkokten, H. Garcia-Molina, and A. Paepcke. Efficient web form entry on pdas. In *Proc. Int'l. World Wide Web Conf. (WWW)*, pages 663–672, 2001.
17. R. Khare and Y. An. An empirical study on using hidden markov model for search interface segmentation. In *Proc. Int'l. Conf. on Information and Knowledge Management (CIKM)*, pages 17–26, 2009.
18. R. Khare, Y. An, and I.-Y. Song. Understanding deep web search interfaces: A survey. *Sigmod Records*, 39(1):33–40, 2010.
19. J. Lehmann, T. Furche, G. Grasso, A.-C. N. Ngomo, C. Schallhart, A. Sellers, C. Unger, L. Böhmann, D. Gerber, D. L. Konrad Höffner and, and S. Auer. Deqa: Deep web extraction for question answering. In *Proc. Int'l. Semantic Web Conf. (ISWC)*, 2012.
20. J. Madhavan, D. Ko, L. Kot, V. Ganapathy, A. Rasmussen, and A. Halevy. Google's deep web crawl. In *Proc. Int'l. Conf. on Very Large Data Bases (VLDB)*, pages 1241–1252, 2008.
21. A. Maiti, A. Dasgupta, N. Zhang, and G. Das. Hdsampler: revealing data behind web form interfaces. In *Proc. Symp. on Management of Data (SIGMOD)*, pages 1131–1134, 2009.
22. I. Navarrete, A. Morales, M. Cardenas, and G. Sciavicco. Spatial reasoning with rectangular cardinal relations - the convex tractable subalgebra. In *Annals of Mathematics and Artificial Intelligence*, 2012.
23. H. Nguyen, T. Nguyen, and J. Freire. Learning to extract form labels. In *Proc. Int'l. Conf. on Very Large Data Bases (VLDB)*, pages 684–694, 2008.
24. T. H. Nguyen, H. Nguyen, and J. Freire. PruSM: a prudent schema matching approach for web forms. In *Proc. Int'l. Conf. on Information and Knowledge Management (CIKM)*, pages 1385–1388, 2010.
25. F. Niu, C. Zhang, C. Re, and J. Shavlik. DeepDive: Web-scale knowledge-base construction using statistical learning and inference. In *Proc. Very Large Data Search (VLDS)*, pages 25–28, 2012.
26. T. Pedersen, S. Patwardhan, and J. Michelizzi. Wordnet::similarity - measuring the relatedness of concepts. In *Proc. HLT-NAACL-Demonstrations*, pages 38–41, 2004.
27. S. Raghavan and H. Garcia-Molina. Crawling the hidden web. In *Proc. Int'l. Conf. on Very Large Data Bases (VLDB)*, pages 129–138, 2001.
28. D. Shestakov, S. Bhowmick, and E. Lim. Deque: querying the deep web. *Data & Knowledge Engineering (DKE)*, 52(3):273–311, 2005.
29. W. Su, J. Wang, and F. H. Lochovsky. ODE: Ontology-assisted data extraction. *ACM Transactions on Database Systems*, 34(2):12:1–12:35, 2009.
30. J. Wang and F. H. Lochovsky. Data extraction and label assignment for web databases. In *Proc. Int'l. World Wide Web Conf. (WWW)*, pages 187–196, 2003.
31. J. Wang, J.-R. Wen, F. Lochovsky, and W.-Y. Ma. Instance-based schema matching for web databases by domain-specific query probing. In *Proc. Int'l. Conf. on Very Large Data Bases (VLDB)*, pages 408–419, 2004.
32. W. Wu, A. Doan, C. Yu, and W. Meng. Modeling and extracting deep-web query interfaces. In *Advances in Information & Intelligent Systems*, pages 65–90, 2009.
33. W. Wu, C. T. Yu, A. Doan, and W. Meng. An interactive clustering-based approach to integrating source query interfaces on the deep web. In *Proc. Symp. on Management of Data (SIGMOD)*, pages 95–106, 2004.
34. X. Yuan, H. Zhang, Z. Yang, and Y. Wen. Understanding the search interfaces of the deep web based on domain model. In *Proc. Int'l. Conf. on Computer and Information Science*, pages 1194–1199, 2009.
35. Z. Zhang, B. He, and K. C.-C. Chang. Understanding web query interfaces: Best-effort parsing with hidden syntax. In *Proc. Symp. on Management of Data (SIGMOD)*, 2004.